NEAR EAST UNIVERSITY
INSTITUTE OF GRADUATE STUDIES
DEPARTMENT OF BUSINESS ADMINISTRATION

ASSESSING THE IMPACT OF USING MACHINE LEARNING ON RATIONAL DECISION MAKING IN DIGITAL TRANSFORMATION CASE STUDY: E-GOVERNMENT AT JORDAN

PHD THESIS

AYAT SALEM

NICOSIA
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ACCEPTANCE/APPROVAL

We certify that we have read the thesis submitted by Ayat Salem titled "**ASSESSING THE IMPACT OF USING MACHINE LEARNING ON RATIONAL DECISION MAKING IN DIGITAL TRANSFORMATION CASE STUDY: E-GOVERNMENT AT JORDAN** " and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of PhD of business administration.

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DECLARATION

I **AYAT SALEM**, hereby declare that this dissertation entitled "ASSESSING THE IMPACT OF USING MACHINE LEARNING ON RATIONAL DECISION MAKING IN DIGITAL TRANSFORMATION CASE STUDY: E-GOVERNMENT AT JORDAN" has been prepared by myself under the guidance and supervision of **Prof. Dr. Serife Eyupoglu** Dean, Faculty of Economics and Administrative Sciences and Chair, Department of Business Administration in the Near East University, Graduate School of Social Sciences regulations and does not to the best of my knowledge breach Law of Copyrights and has been tested for plagiarism and a copy of the result can be found in the Thesis.

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DEDICATION

This dissertation honors the memory of my mother (RIP).

Abstract

“ASSESSING THE IMPACT OF USING MACHINE LEARNING ON RATIONAL DECISION MAKING IN DIGITAL TRANSFORMATION CASE STUDY: E-GOVERNMENT AT JORDAN”

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This study examines the growing impact of AI, specifically machine learning (ML), on rational decision-making (RDM) within the Jordanian e-government sector, emphasizing the mediating role of trust. By leveraging supervised and unsupervised ML techniques, e-government systems can enhance data collection, increase the accuracy of analysis, expedite the evaluation of decision options, and improve risk assessments. The research employs a quantitative approach, utilizing a structured questionnaire distributed to 163 employees in the Jordanian e-government sector. Data analysis was conducted using SPSS v25 and AMOS v23 to perform mediation analysis. Results reveal that ML positively influences RDM in e-government, with trust acting as a crucial mediator in the successful integration of ML into decision-making. Trust amplifies the benefits of ML, fostering its adoption in public administration. The study underscores the importance of building trust to ensure the effective and sustainable use of ML in the digital transformation of government services. While limitations exist, the findings offer valuable insights for researchers and policymakers, advancing sustainable practices in the e-government domain.

Keywords: machine learning; supervised machine learning; unsupervised machine learning; rational decision making; trust; e-government.

Özet

"MAKİNE ÖĞRENİMİNİN DİJİTAL DÖNÜŞÜMDE RASYONEL KARAR VERME ÜZERİNDEKİ ETKİSİNİN DEĞERLENDİRİLMESİ VAKA ÇALIŞMASI: ÜRDÜN E-DEVLET"

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Doktora, İşletme Yönetimi Bölümü

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Bu çalışma, Ürdün e-devlet sektöründe yapay zekânın (YZ), özellikle makine öğreniminin (MÖ), rasyonel karar verme (RKM) üzerindeki artan etkisini ve güvenin aracı rolünü incelemektedir. Denetimli ve denetimsiz MÖ tekniklerinden faydalanarak, e-devlet sistemleri veri toplama süreçlerini geliştirebilir, analiz doğruluğunu artırabilir, karar seçeneklerinin değerlendirilmesini hızlandırabilir ve risk değerlendirmelerini iyileştirebilir. Araştırma, Ürdün e-devlet sektöründe çalışan 163 personele dağıtılan yapılandırılmış bir anket kullanılarak nicel bir yaklaşımı benimsemiştir. Veriler, SPSS v25 ve AMOS v23 kullanılarak aracılık analizi ile değerlendirilmiştir. Sonuçlar, MÖ'nün e-devlette RKM üzerinde olumlu bir etkisi olduğunu ve güvenin, MÖ'nün karar verme süreçlerine başarılı bir şekilde entegre edilmesinde kritik bir aracı rol oynadığını ortaya koymaktadır. Güven, MÖ'nün faydalarını artırarak kamu yönetiminde benimsenmesini teşvik etmektedir. Çalışma, MÖ'nün hükümet hizmetlerinin dijital dönüşümünde etkili ve sürdürülebilir bir şekilde kullanılmasını sağlamak için güven inşa etmenin önemini vurgulamaktadır. Bazı sınırlamalar bulunsa da, elde edilen bulgular araştırmacılara ve politika yapıcılara değerli bilgiler sunarak e-devlet alanında sürdürülebilir uygulamaları ilerletmektedir.

Anahtar Kelimeler: makine öğrenimi; denetimli makine öğrenimi; denetimsiz makine öğrenimi; rasyonel karar verme; güven; e-devlet.

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List of Abbreviations

AI: Artificial intelligence

MoDEE: Ministry of Digital Economy and Entrepreneurship

DT: Digital Transformation

e-government: Electronic Government

ML: Machine Learning

SML: Supervised Machine Learning

NLP: Natural Language Processing

NEU: Near East University

RDM: Rational Decision Making

SETAM: Science, Engineering, Technology, Art and Mathematics

UNSML: Unsupervised Machine Learning

IoT: Internet of Things

CHAPTER I

Introduction

Artificial intelligence (AI) technology, particularly machine learning (ML), has emerged as a transformative instrument in various sectors, enabling governments to improve decision-making, reduce costs, enhance efficiency, and offer tailored services. This research identifies the main impact of implementing ML algorithms and techniques on the decision-making process, especially rational decision-making (RDM), within the digital transformation (DT) efforts implemented at the e-government of Jordan. As governments adopt digital technologies, the ability to analyze large, complex datasets through machine learning provides significant opportunities to optimize processes, enhance service delivery, and improve public trust. The goal is to understand how ML can support more informed decisions, improve efficiency, reduce costs, and strengthen public trust, ultimately driving innovation and better governance in Jordan's e-government sector. Furthermore, the research seeks to explore the role of trust refers to the main factor that bridges as a mediating variable of the correlation between (ML and RDM). By understanding these influences, this research will provide insights into how machine learning can be leveraged to support Jordan's broader goals of digital transformation decisions and improve governance outcomes.

Statement of the Problem

Artificial intelligence (AI) has been around for almost sixty years, but its advancement has resulted in applications that have significantly impacted our lives. Artificial intelligence is duplicating and modifying human intelligence to develop intelligent machines (Duan et al., 2019; Sharma et al., 2020). Artificial intelligence systems are evolving quickly and are increasingly used in managing. Government leaders and managers are facing the challenges of decision-making and massive volume of data that need to be analyzed, taking into consideration the rational choices mixed with human experience in decision-making (Janssen et al., 2022)

The manager's capacity to balance rational decisions is critical to tactical and strategic decisions. AI technology is growing in a significant way; this is primarily because these technologies have proven to reduce administrative overhead and help administrators make data-based decisions rather than relying on them for intuitive decision-making. Some researchers claim that artificial intelligence can reasonably think and act (Al-Mushayt, 2019; Piscopo et al., 2017 ; Janssen et al., 2020; Nortje &

Grobbelaar, 2020) they are more cautious, behave like humans, and do not share the same opinion about their ability to overcome obstacles and barriers to thinking (Sun & Medaglia, 2019 ; Wirtz & Müller, 2019 ; Pereira et al., 2017 ; Alkhwaldi et al., 2017) Science, mathematics, philosophy, psychology, linguistics, and computer science are all rooted in Artificial Intelligence.

AI research in the governmental sector is currently in its formative stages. It is in the early phases of development, where foundational concepts, methodologies, and applications are still being established. There is significant opportunity for empirical research on the applications and challenges of both natural and artificial intelligence, particularly concerning the stakeholders involved in the government sector (Androutsopoulou et al., 2019, Pereira et al., 2017; Alkhwaldi et al., 2017). Turing Machine is an ideal intelligent computer model, which developed an automata theory and was introduced by Alan Turing. This model became an essential milestone in the study of AI, and other researchers got interested in creating a "thinking machine" that can reason like humans (Sharma et al., 2020; de Sousa et al., 2019).

AI has enormous potential in a variety of governmental fields, including healthcare, education, public transport, infrastructure, data protection and management, digitalization, mobility, telecommunications, finance, regulation formulation, governance strategy, and the legal framework and justice administration, research, and development, among others. Governments must consider and integrate it to improve the efficiency of governmental decisions. Additionally, artificial intelligence has many applications in diverse areas, such as security and safety, protection, and prophetic maintenance planning for earthquakes and other pandemics or disasters (Sun & Medaglia, 2019).

There are many components of artificial intelligence; researchers used the most common six components as the following: Machine Learning (ML) is a division of artificial intelligence that empowers systems to acquire knowledge from data and progressively refine their performance through increased exposure to information. Within this field, **Neural Networks** are inspired by the human brain's structure and are used for pattern recognition and predictions in complex datasets. **Natural Language Processing (NLP)** focuses on the interaction between computers and humans through language, allowing for applications like chatbots and translation. **Expert systems** mimic human decision-making in specific domains by using a knowledge base and inference rules. **Computer vision** enables machines to interpret visual information, facilitating facial recognition and image classification tasks. Lastly, **Robotics** combines AI with the design and operation of robots to perform tasks autonomously across various industries. Together, these technologies create advanced AI systems capable of addressing various challenges. In this study, we will study machine learning (ML) as the most common component of artificial intelligence (Vrbka & Rowland, 2020; Karatas & Budak, 2022; Kureljusic & Metz, 2023; Varma et al., 2021).

Machine learning can be classified into two primary categories: supervised (SML) and unsupervised (UNSML). Starting from supervised machine learning involves extracting knowledge from a dataset where the outcomes are already pre-defined. Conversely, unsupervised machine learning focuses on uncovering insights from a dataset without pre-defined outcomes. For example, unsupervised learning can categorize customers into different profiles and lifestyles without any prior information regarding the number of profiles or the specific customers associated with each profile (Kureljusic & Metz 2023; Varma et al., 2021).

On the other hand, the government, for monitoring purposes to raise public awareness and encourage active citizen involvement in government (Al-Mushayt, 2019), may use such information. In addition, the government faces numerous technological, operational, financial, and policy challenges when AI is considered to have a high potential that may be used in several applications (Halaweh, 2018). The government sector's artificial intelligence research is still in its premature stages, which covers the expected impacts, which is still in theoretical. There is a lot of room for theoretical work on artificial intelligence implementations and challenges, as government stakeholders believe (de Sousa et al., 2019). A significant number of researchers have only discussed the technical dimensions of AI implementations, which seems hazy in the absence of a rigorous governmental model that depicts the consequences for administrative state governance (Halaweh, 2018; Piscopo et al., 2019). Furthermore, there is an increasing demand for a thorough understanding of the range, challenges, and limitations of AI-based applications and their overall impact.

Despite advancements in AI, the government continues to provide services in an antiquated manner. Jordanian Customs as a test case (Al-A’wasa, 2018), which may be a reflection of public budget allocation, as most resources are geared toward maintaining legacy systems (Kumar & Kalse, 2021). Citizens' trust and satisfaction with public services may be harmed because of this circumstance, especially when the citizens think of comparing it with private sector services (Al-A'wasa, 2018; Ghimire et al., 2020; Kumar& Kalse, 2021). Paliukas and Savanevičienė, 2018 proposed a hybrid approach to solve the lack of more exhaustive and contextual knowledge in Artificial Intelligence solutions by integrating humans and machines to make so-called "superior decisions".

Additionally, numerous ethical, legal, and social barriers hinder integrating artificial intelligence solutions in the government services. These obstacles primarily stem from concerns about job displacement due to automation and citizens' distrust in artificial intelligence (Oumkaltoum & Mahmoud 2019; Bader & Kaiser, 2019).

Despite the using AI new technologies in many various sectors such as health, industry, and education, the researchers also investigate the field of administrative science studies, especially in decision making; Simon's decision-making model is based on three phases: intelligence, analysis & design, and choice, according to the rational decision-making perspective (Simon,1997). The intelligence phase involves identifying and defining the problem or situation that requires a decision. Once the problem is understood, alternative solutions are generated in the analysis and design phase, and then evaluated in the choice phase to select the best alternative. While machine learning may assist a decision support system (DSS) in one or more stages, DSS is designed to support decision-makers rather than make decisions for them.

Therefore, this work uses Simon's original three-phase model to suggest which phase machine learning best supports and which ML techniques suit each decision-making phase. The phases are defined as below:

- The first phase is the "intelligence gathering phase.” At this stage, the decision-maker identifies the problem or decision to be made and gathers all relevant information about it. This includes collecting data, analyzing trends, and evaluating possible solutions.
- The second phase is the "analysis and design phase." At this stage, the decision-maker evaluates and analyzes the gathered information. They may use different methods, such as SWOT analysis, to evaluate the different options, determine the optimal course of action, and set the alternatives.
- The final phase is the "choice phase." At this stage, the decision-maker chooses the most suitable alternative based on the information analyzed in the previous phases. The decision is then implemented, and the results are monitored and evaluated to determine whether the decision was effective.

Research Purpose

This work purposed to explain the main influence of using machine learning on the rational decisions taken regarding the DT in Jordanian e-government. For many years, AI technology has been utilized across various industries to enhance decision-making and problem-solving processes more efficiently. Many aspects, such as reducing costs, reducing the workload of civil servants, improving efficiency and developing new jobs, solving resource allocation problems, providing public services, improving citizen satisfaction personalization and 24/7 availability (Sun & Medaglia, 2019; Androutsopoulou et al., 2019).

AI technology aims to enhance the experience by improving response quality and speed, providing 24/7 support, and reducing administration costs. This research aims to explore how using of ML applications has the potential to enhance the process of deciding on the framework of government digitalization evolution. Specifically, the study will investigate how machine learning techniques can be applied to the large and complex datasets produced by digital technologies to extract valuable insights and inform decision-making processes. Digital transformation involves the utilization of digital technologies to change business operations, and this study aims to explore how machine learning can facilitate this transformation. By employing machine learning techniques to evaluate large datasets and detect patterns and tendencies, decision-makers can make more informed choices, optimize business processes, and enhance overall performance metrics. Ultimately, the goal of this research is to assist governments in recognizing how they can leverage machine learning to meet their digital transformation objectives and foster innovation in e-government operations.

The application of ML in government can benefit society as a whole and create public value. By using machine learning in governments, governments can address issues such as resource shortages, operational scale, and government standardization of distribution systems. The benefits of using artificial intelligence in government are related to the benefits of decision-making. ML can assist government decision-makers in making more informed and accurate decisions. By using artificial intelligence for management, decision-makers can show potential areas of action. In general, artificial intelligence is expected to reduce the administrative burden, and algorithmic big data systems enable automated decision-making in public institutions and benefit of engagement between government and citizens. Machine learning applications have the potential to enhance public confidence and satisfaction by improving the efficiency and effectiveness of services provided by governmental and public organizations. By utilizing ML applications and algorithms, these organizations can analyze huge amount of data to make informed decisions, anticipate citizen needs, and deliver personalized services.

Research Objectives

This research primarily examines how machine learning, incorporating subcategories of ML (supervised and unsupervised) techniques, influences RDM. The rational decision-making process includes three phases: first, the intelligence gathering phase; second, the analysis and design phase; and the final choice phase. Furthermore, the study will investigate if trust mediates in the correlation between ML and RDM. To achieve these goals, the study will focus on five specific objectives:

1. Assess the influence of SML on RDM, covering the three phases: intelligence gathering, analysis and design, and choice, within the digital transformation in Jordan's e-government.
2. Evaluate the influence of UNSML on RDM, covering the three phases: intelligence gathering, analysis and design, and choice, within the digital transformation in Jordan's e-government.
3. Examine how SML and UNSML influence trust within the digital transformation in Jordan's e-government.
4. Assess the effect of trust on RDM, covering the three phases: intelligence gathering, analysis and design, and choice, within the digital transformation in Jordan's e-government.
5. Examine if trust mediates the correlation between ML (supervised and unsupervised) and RDM, covering the three phases: intelligence gathering, analysis and design, and choice, within the digital transformation in Jordan's e-government.

Research Questions

The main question of the current research is the following: What is the influence of using ML (SML & UNSML) on RDM - including the three phases (intelligence gathering, analysis & design, and choice) considering the mediating effect of trust in the proposed relationship within the digital transformation in Jordan's e-government.? Accordingly, this research will seek to address the following five questions:

1. What is the influence of SML on RDM- including (intelligence gathering, analysis & design, and choice) within the context of digital transformation in Jordan's e-government.?
2. What is the influence of UNSML on RDM- including (intelligence gathering, analysis & design, and choice) within the context of digital transformation in Jordan's e-government.?
3. What is the influence of ML on the trust within the context of digital transformation in Jordan's e-government.?
4. What is the influence of the trust on the RDM - including (intelligence gathering, analysis & design, and choice) within the context of digital transformation in Jordan's e-government?
5. Is there any mediating role of the trust on the relationship between ML (both supervised and unsupervised) on the RDM - including (intelligence gathering, analysis & design, and choice) within the context of digital transformation in Jordan's e-government?

Significance of Study

The government's Artificial intelligence research is still in its early stages, and it only looks at the expected effects of Artificial intelligence, which is theoretical. There are many areas for theoretical work on artificial intelligence applications and challenges, as well as the stakeholders working in the governmental sector.

The contribution of this study is to offer insights and recommendations for governments seeking to harness ML to enhance their RDM processes within the digital transformation framework. Some specific contributions could include:

- Identify critical areas where ML can be utilized to improve RDM in digital transformation. The study could identify specific use cases where machine-learning algorithms can be applied to large and complex datasets to extract insights that can inform decision-making.
- Evaluation of the advantages of employing ML for RDM in digital transformation. The study could provide a comprehensive evaluation of the benefits that the government can expect to see from using machine-learning algorithms, such as improved accuracy and efficiency in decision-making, better risk management, and increased competitiveness.

- Identification of potential challenges and limitations associated with using machine learning for decision-making in digital transformation. The study could also highlight potential challenges and constraints organizations may face when implementing machine-learning algorithms, such as data quality issues, specialized skills, and ethical considerations.
- Recommendations for organizations looking to implement machine learning in digital transformation. The study could provide practical recommendations for organizations looking to implement machine learning algorithms in their decision-making processes, such as guidance on selecting appropriate algorithms, building the necessary infrastructure, and adhering to regulations and ethical standards.

Before this research, some researchers claimed that artificial intelligence technologies have the potential to think and act rationally, while others are more cautious and do not share the same opinion on their ability, obstacles, and barriers to behaving and thinking like humans. On the other hand, there is a debate among researchers about the value gained from artificial intelligence technologies compared with the cost of applying where this research will highlight the trade-off in the expected costs. In this research, we are looking for how using artificial intelligence technologies can also impact decisions taken to improve the digital transformation process. A study on machine learning's impact on decision-making for digital transformation would provide valuable insights and recommendations that can help government leverage machine learning to drive innovation and improve their service delivery operations in the digital age. The findings of a meta-analysis will be used to highlight the flaws in prior research and make recommendations for how to improve the design of future studies.

Limitations

However, this research will show that they are still in its early stages, and it only looks at the expected effects of artificial intelligence mainly machine learning, which is theoretical in nature. There is a lot of space for empirical research on machine learning applications and challenges, as well as by the stakeholders working in the government sector. That’s why there is a need for more research. Inside of that, no real attention was paid to the rapid changes in technology all around the world to be synchronized with the slowness of changes in the technologies used in government.

There are several limitations to this project, starting from the fact that the government's AI research is still in its early stages, and it only looks at the expected effects of AI, which is theoretical in nature. High cost of implementation for setting up AI-based machines; this process is extremely time, cost, and resource-consuming. On the other hand, if the model is not properly validated during training, it can lead to overfitting, adding more random noise than the actual data, retaining the model that cannot be generalized, and adopting new technologies.

Summary

This chapter introduces the role of artificial intelligence (AI), particularly ML, in transforming government sectors by improving RDM. It explains how governments like Jordan can leverage ML to enhance efficiency, reduce costs, and improve public trust through digital transformation (DT). The chapter outlines the research problem, which focuses on the gap between AI's theoretical advancements and its practical applications in government decision-making, aiming to investigate the potential of ML in improving governance and decision-making processes.

CHAPTER II

Literature Review

Theoretical Framework

A comprehensive review of the relevant literature is presented in this chapter, outlining major trends, debates, and gaps that inform the research question at hand. By analyzing the contributions of past studies, the literature review serves as a roadmap for positioning the current research within the broader academic discourse. The aim of this chapter is to investigate the current opportunities and offer a contextual foundation for the research. It begins by defining the key concepts central to the study (ML, RDM, trust, and digital transformation in an e-government context), followed by a discussion of theoretical frameworks and methodologies used in prior research. The chapter then delves into the findings of empirical studies that have addressed similar or related relationships, highlighting both the consensus and areas of divergence in the field. In doing so, it also identifies gaps in the literature where further investigation is needed, establishing the significance of the present study.

Machine Learning

Machine learning (ML), a fast-growing discipline in computational algorithms, strives to emulate human intelligence by learning and adapting from data inputs, making it a vital resource in the big data era. Machine learning (ML) has a broad range of applications, spanning fields such as economics, computer vision, engineering, biomedical sciences, entertainment, and many other domains (Alloghani et al., 2020; Pugliese et al., 2021; Sen et al., 2020). It tackles the issue of creating computers that can enhance their performance autonomously by learning from their experiences. Situated at the crossroads of computer science and statistics, machine learning is a fundamental component of artificial intelligence and the science of data, making it one of the most rapidly advancing fields today. Recent progress in ML has been propelled by the creation of innovative learning algorithms, supporting theories, increased access to online data, and affordable computing resources. Data-driven ML techniques are now widely adopted in numerous industries, including STEAM (science, technology, engineering, art, and mathematics) and, more recently, in commerce. This transition has marked the beginning of a new age of decision-making grounded in evidence decision-making across numerous areas such as education, healthcare, economics, financial modeling, tourism, marketing, law, and manufacturing (Wang et al., 2018; Sen et al., 2020; Broby, 2022; Loukili et al., 2023).

The history of ML is a dynamic and evolving story that stretches over several decades. Its origins date back to the mid-20th century, when foundational concepts and early innovations paved the way for its modern applications. As a distinct branch of artificial intelligence, machine learning concentrates on instructing machines to learn and adapt independently from data (Pugliese et al., 2021). In contrast, AI is a broader scientific discipline focused on replicating human capabilities. Within AI, machine learning, as a methodology, imparts the ability for computers to learn from their prior encounters. Oppositely to traditional models that rely on predefined equations, machine learning functions derive perceptions directly from the mass of data using algorithms and techniques. These algorithms enhance their capability flexibly as the scale of learning cases escalates, continually refining their proficiencies at the long run (Sen et al., 2020).

Machine learning's recent advancements owe much to novel learning algorithms and the increasing availability of online data, as well as low-cost computing resources. Its data-driven techniques have widespread applications in various fields (Wang et al., 2018; Alexopoulos et al., 2019; Pugliese et al., 2021). For a real-life example, for health care in cancer treatment, where over half of patients receive radiotherapy, a pivotal modality in advanced stages, the complexity of processes extends from consultation to treatment and beyond. Integrating machine learning algorithms is advantageous for optimizing and automating complex tasks in radiotherapy, including quality assurance in radiation physics, contouring and treatment planning, image-guided radiotherapy, outcomes prediction, and treatment response modeling. The ability of ML to learn from current contexts and leverage that knowledge for new tasks presents considerable potential for improving the safety and effectiveness of radiotherapy practices, ultimately resulting in better patient outcomes (El Naqa & Murphy, 2022).

ML is categorized into two main types: supervised and unsupervised (Alloghani et al., 2020). In supervised machine learning (SML), the algorithm is trained on labeled data, where the inputs and corresponding outputs are predefined. This enables the model to understand the relationships between them and make predictions when encountering new data. This method is commonly used for tasks like classification and regression, such as predicting prices or classifying emails (Sen et al., 2020). Conversely, UNSML works with non-classified data that is unlabeled, where the algorithm must find patterns or groupings on its own. This approach is often applied in clustering and anomaly detection, such as grouping users based on purchasing behavior or detecting abnormal patterns in network traffic. Both types are crucial in numerous real-world applications, enabling machines to make informed decisions depending on the data attributes they process (Usama et al., 2019).

Supervised Machine Learning (SML)

SML is a branch of AI technologies dedicated to developing models and algorithms that can recognize trends and generate predictions or classifications using labeled training data. In SML, a model is learned from a known dataset that includes input features and their related output labels. The objective is for the model to recognize the underlying patterns or find out if the inputs have a relation with outputs, allowing it to accurately predict outcomes for new, previously unseen data (Sen et al., 2020).

Fundamental concepts of supervised machine learning are summarized as data representation, training, and testing (Pugliese et al., 2021; Sen et al., 2020); the data representation in supervised learning is represented as a set of examples, each consisting of input variables and their associated output labels. The input features form the "cause" variables, and the output labels are the "effect" variables that the model intends to predict. Meanwhile, training and testing: the dataset is typically divided into a training set utilized to teach the model and a testing set used to examine its efficiency and productivity on hidden data. This division helps examine the model's generalization ability (Pugliese et al., 2021; Sen et al., 2020).

There are many mathematical frameworks that are crucial and well explained as hypothesis space; supervised learning requires defining a hypothesis space, which represents the collection of potential functions the model can learn. The goal is to identify the hypothesis that not only aligns closely with the training data but also extends effectively to unseen data. In addition to the hypothesis space, the loss function is crucial as it measures the error between the model's predictions and the actual labels. Throughout the training process, the model fine-tunes its parameters to minimize this loss, thereby enhancing its performance (Jiang et al., 2020).

A variety of algorithms and models are utilized from SML, with some of the most popular being Linear Models**,** Decision Trees, and Neural Networks. Linear models, such as linear regression and logistic regression, are foundational techniques used for regression and classification tasks, respectively. These models operate under the assumption that there is a linear relationship between the input features and the output (Raschka & Mirjalili, 2019). Decision Trees are structured like a tree, where each internal node signifies a decision or test based on a particular feature, and each leaf node corresponds to a predicted output or label. Ensemble methods, such as Random Forests, improve predictive accuracy by combining multiple decision trees, reducing overfitting, and enhancing overall performance (Breiman, 2017). On the other side, Neural Networks, especially deep learning, have gained significant importance over the past few years. These models are made up of layers of interconnected nodes (neurons) that analyze and modify input data. By learning complex patterns and hierarchical representations, neural networks are extremely effective in handling tasks such as image recognition, natural language processing, and speech recognition. Their capacity to represent non-linear relationships renders them powerful tools for both regression and classification tasks. They are composed of interconnected layers of neurons, enabling them to learn complex hierarchical representations (Jiang, et al., 2020). These models and algorithms are evaluated using well-defined Evaluation Metrics: Accuracy, Precision, and Recall.

Powers (2020) defined these metrics as quantifying various aspects of a model's performance. Accuracy measures the overall correctness of a model's predictions by calculating the ratio of correct predictions to the total number of predictions. On the other hand, precision evaluates the model's capability to make precise positive predictions, reflecting the proportion of true positive predictions out of all positive predictions.

In conclusion, SML stands as a cornerstone in the realm of AI, providing a robust context for building predictive models. By carefully aligning labeled input features with their corresponding output labels, the model learns to identify connections between the two, these algorithms unravel complex relationships and complicated patterns within data, enabling them to make optimal forecasts on hidden and unseen instances. The theoretical foundations, encompassing key concepts such as data representation, mathematical frameworks, diverse algorithms, and evaluation metrics, form a comprehensive framework that has fueled substantial advancements in various domains. Despite its successes, supervised learning faces ongoing obstacles, comprising the demand for superior labeled data, potential overfitting, and the interpretability of increasingly complex models. As researchers delve into these challenges and explore new avenues, the theoretical underpinnings of supervised machine learning remain integral to shaping its evolution and fostering its applications across diverse fields.

Unsupervised Machine Learning (UNSML)

UNSML is a subcategory of ML derived from AI focused on algorithms that uncover patterns and search for correlations, relationships, or structures within data without the need for explicitly labeled or classified outputs. In UNSML, the algorithm examines the foundational structure of the data to uncover significant trends or groupings. This process involves identifying clusters or associations that may not be immediately apparent, allowing for deeper insights into the dataset. By leveraging techniques such as clustering and dimensionality reduction, unsupervised learning enables the discovery of intrinsic relationships within the data, laying the groundwork for further application or analysis. Also, clustering is a common task in unsupervised learning where data is grouped into clusters based on similarities (Alloghani, et al., 2020; Nielsen, 2022).

Assessing unsupervised learning algorithms can be difficult because there are no predefined labels to directly measure the accuracy of predictions. Instead, alternative evaluation methods, such as measuring the consistency of discovered patterns or comparing results across different metrics, are often required. One of the challenges in unsupervised learning is defining meaningful metrics for evaluating the performance of algorithms since there are no explicit ground truth labels. Understanding the outcomes of unsupervised learning algorithms can be intricate, especially in tasks like clustering where the interpretation of clusters may not always be straightforward. Without clear output labels to validate the results, understanding whether the discovered patterns or groupings are meaningful requires additional analysis, often using subjective or domain-specific insights. Furthermore, multiple factors like data distribution, algorithmic assumptions, and the choice of parameters can influence the final interpretation, making it more challenging to extract concrete conclusions compared to supervised learning. With the increasing complexity of data, handling high-dimensional datasets efficiently and effectively remains a challenge in unsupervised learning (Usama, et al., 2019; Nielsen, 2022).

This leads to the conclusion that the theoretical foundation of UNSML revolves around recognizing patterns and finding correlations and relationships within data without depending on predefined labelled outputs. Key concepts include clustering, dimensionality reduction, association rule mining, and the development of meaningful evaluation metrics. Challenges include defining appropriate metrics and interpreting results, and ongoing research seeks to tackle these challenges and extend the capabilities of unsupervised learning methods.

Rational Decision Making (RDM)

RDM is a fundamental concept in wide fields and has been explored through diverse theoretical lenses. One prominent framework is based on the classical economic model, which assumes that decision-makers are rational actors aiming to maximize utility. These concepts have a long history of development, with significant advancements dating back to the final decades of the 18th century, significant changes were taking place in the economic, social, and political landscape. This period marked the beginning of the Industrial Revolution, a transformative era that shifted the economy from agrarian-based to industrial and manufacturing-based Adam Smith suggests his theory of the classical economic model claiming that individuals make decisions by systematically evaluating the costs and benefits of various options in order to maximize their overall satisfaction or utility (Elsner, 1989). This model assumes rational behavior, where individuals are fully informed, and each decision is made with the intent of achieving the greatest personal advantage or happiness. This framework underlies many traditional economic theories and emphasizes utility maximization as the guiding principle for decision-making processes (Stirati,1994). Critics argue that this model often oversimplifies decision processes, assuming perfect information, unbounded rationality, and consistent preferences. However, challenges to this idealized view have led to the development of alternative theories that account for cognitive limitations, psychological biases, and the complexity of decision environments (Robinson & Dow, 2021).

Herbert Simon's theory of bounded rationality represents a significant departure from the classical economic model of decision-making. In his seminal work, "Administrative Behavior", Simon critiques the assumption of full rationality in classical models, which posit that individuals always make decisions by thoroughly evaluating all available options to maximize utility. Instead, Simon argues that real-world decision-makers operate under cognitive limitations such as limited information, time constraints, and finite cognitive capacity. Due to these constraints, individuals often pursue satisficing—a strategy where they seek a solution that is "good enough" rather than optimal (Simon, 1979). This approach recognizes that decision-makers cannot realistically process every piece of information or forecast all potential outcomes, leading them to settle for a decision that meets their acceptable standards rather than the theoretical best. Simon's theory reshaped how economists and psychologists view decision-making, particularly in complex environments where perfect rationality is unrealistic. His contributions are foundational in fields like behavioral economics and organizational theory (Rubinstein, 1998). By acknowledging these constraints, bounded rationality has become a foundational concept for understanding how decisions are made in real-world situations, significantly influencing the development of behavioral economics and related disciplines. Simon's theory serves as a cornerstone, challenging idealized models and paving the way for a more realistic understanding of how individuals and organizations make choices (Simon, 1990).

This was followed by Prospect Theory this theory introduces a more psychologically accurate model, highlighting how people perceive gains and losses asymmetrically, often leading to irrational behaviors like loss aversion (Kahneman & Tversky, 2013). From another point of view, the Decision Heuristics theory explained that these are mental shortcuts that people use to make quick, often imperfect decisions. They include strategies like availability, anchoring, and representativeness heuristics, which shape decisions in complex situations (Gigerenzer & Gaissmaier 2011).

By reviewing the theoretical landscape of rational decision-making we found it very vast, shaped by various disciplines, including economics, psychology, and organizational theory. This diversity stems from the exploration of different perspectives on how individuals and organizations make choices, particularly under uncertainty and cognitive limitations. Scholars continue to refine these theories and explore how they can be integrated to better understand the dynamic and context-dependent nature of decision-making. By drawing from these diverse approaches, a more comprehensive and realistic framework of human decision-making is emerging, one that acknowledges the complexities and limitations inherent in the process. By analyzing rational decision-making from various theoretical perspectives, we can conclude that it unfolds through three primary phases, as outlined by Simon (1979): The Intelligence Gathering Phase, the Analysis and Design Phase, and the Choice Phase. Intelligence Gathering Phase: In this initial phase, decision-makers focus on collecting relevant data and information to understand the problem's context. This step involves identifying the issue, setting evaluation criteria, and gathering necessary resources for further analysis (Nutt, 2007; Uzonwanne, 2023; Wiener, 2019). Analysis and Design Phase: During this phase, decision-makers process and evaluate the collected data. Analytical tools such as SWOT analysis, cost-benefit analysis, or risk assessment are often employed to identify patterns and generate potential solutions (Power et al., 2019). This phase helps frame the problem with a structured approach to assess alternatives. And Choice Phase: In the final phase, decision-makers select the most viable alternative based on their analysis, considering both the immediate and long-term outcomes. Once the decision is made, the solution is implemented, and continuous monitoring ensures its effectiveness (Kahneman & Tversky, 2013; Bag et al., 2021). This structured approach to rational decision-making ensures a thorough evaluation of options, enhancing the capacity for informed, accountable, and effective decision outcomes across various contexts.

Intelligence Gathering Phase of RDM

The intelligence-gathering phase is the first and foundational step in the (RDM) model. This phase is crucial because it lays the groundwork for all subsequent actions in the decision-making process. It involves systematically gathering relevant data, recognizing the problem or opportunity, and defining the context in which the decision will be made. In this step, decision-makers focus on understanding the nature of the decision they need to make by identifying all the variables and factors involved. This includes information gathering (both internal and external), problem recognition, and establishing criteria for evaluating the problem. Without a clear understanding of the decision context, it's impossible to move forward effectively. Therefore, this phase not only highlights the need for comprehensive research but also ensures that all options are considered from the beginning, setting up the framework for the analysis and design phase to follow. A structured intelligence-gathering phase helps ensure that the decision-making process is both informed and purposeful, as seen in models from Herbert Simon (1979) and more recent work by Nutt (2007) and Uzonwanne (2023). By accurately diagnosing the problem or decision context, this phase maximizes the chances of optimizing outcomes in later stages of the RDM process.

Herbert Simon's concept of bounded rationality significantly reshaped our understanding of decision-making. He argued that individuals are limited by cognitive constraints, such as limited time, incomplete information, and finite mental processing abilities. As a result, decision-makers cannot always achieve optimal solutions. Instead, they often settle for decisions that are "good enough" through a process called satisficing (Simon, 1979). In the Intelligence phase, decision-makers gather information that is sufficient to make a satisfactory choice rather than exhaustively searching for the perfect option. This concept aligns with Simon's broader view that human rationality is bounded and constrained by practical realities. From a cognitive psychology perspective, the Intelligence phase parallels information processing theories, which see the mind as a system that processes incoming data in stages—receiving, storing, retrieving, and interpreting information. The Intelligence phase represents the initial stages of this cognitive process, where decision-makers gather and organize information to frame the problem. In organizational contexts, this phase connects to organizational learning (Argyris & Schön, 1997), where organizations systematically scan their environments for information. They assess external opportunities and threats while evaluating internal strengths and weaknesses. The intelligence-gathering process enables organizations to adjust to evolving environments and enhance their decision-making processes, ensuring that decisions are aligned with their strategic goals and environmental realities.

In summary, Simon's concept of bounded rationality highlights the pragmatic nature of decision-making under real-world constraints. It emphasizes that decision-makers gather information sufficient to reach a satisfactory solution, not necessarily the best one. This concept is reinforced by cognitive psychology's information processing models and organizational learning theories.

In the Intelligence phase, decision-makers seek feedback from the environment to understand the consequences of past decisions and to adjust their mental models accordingly. This feedback loop is essential for adapting to changing circumstances and improving decision outcomes (Wiener, 2019). Karl Weick's sense-making theory is relevant to the intelligence phase, as it emphasizes the importance of creating meaning from ambiguous and complex situations. Decision-makers engage in sense-making by collecting information, connecting it to existing knowledge, and developing a unified insight into the problem at hand. This process is iterative and helps shape subsequent decision-making steps (Weick, 1995). The Intelligence phase involves a systematic process of environmental scanning, where decision-makers collect and analyze information about the external environment. This aligns with the strategic management literature, where understanding the external environment is crucial for formulating effective strategies. Overall, the intelligence-gathering Phase maximizes the chances of optimizing outcomes in subsequent stages of the RDM process by ensuring that decisions are informed and grounded in a thorough understanding of the context.

In summary, the theoretical foundation for the intelligence phase of RDM is characterized by information gathering, problem recognition, and a holistic understanding of the decision context, setting the stage for subsequent steps in the decision-making process.

Analysis and Design Phase of RDM

The second step is addressed as the analysis and design phase of RDM, which involves crafting and evaluating potential solutions based on available information and objectives. Several theoretical frameworks contribute to understanding this phase, integrating concepts from decision theory, management science, and organizational behavior (Power et al., 2019). Decision analysis involves systematic approaches to evaluate decision alternatives. It integrates decision trees, probability assessments, and utility functions to quantify uncertainties and trade-offs (Keeney and Raiffa, 1993). One of the main theories discussed in this analysis and design phase is Behavioral decision theory, which incorporates psychological factors into decision-making models, recognizing that individuals may deviate from purely rational choices due to cognitive biases and heuristics (Ariely, 2010; Kahneman and Tversky, 2013). Another theory discussed in this phase is the Game theory, which examined strategic interactions among decision-makers. In decision design, the focus shifts to modeling scenarios where outcomes are influenced not only by an individual's actions but also by the decisions made by others. This interaction between multiple agents is significant in fields such as game theory, where strategic considerations play a vital role (Binmore & Nalebuff, 1992; Osborne & Rubinstein, 1994). One essential approach within this phase is Multi-Criteria Decision Analysis (MCDA), which involves evaluating alternatives based on several criteria. MCDA considers both qualitative and quantitative factors, allowing decision-makers to weigh different aspects of each alternative effectively. This approach is especially beneficial in intricate decision-making scenarios that require trade-offs, as it offers a structured framework for evaluating various options and their consequences (Hwang & Yoon, 1981; von Neumann & Morgenstern, 1944). By integrating insights from game theory with MCDA, decision design can more effectively address the complexities of real-world scenarios, facilitating informed and strategic decision-making.

In summary, the Analysis and Design Phase of rational decision-making is crucial for developing and evaluating potential solutions based on the information at hand and the specific objectives of the decision-makers. By visualizing potential outcomes and assigning values to different scenarios, decision-makers can better understand the implications of their choices. This structured approach not only enhances the clarity of the RDM but also allows for a more informed selection of the best possible solutions, ultimately improving the effectiveness and efficiency of decision-making in complex environments.

Choice Phase of RDM

The Choice Phase is the final step in the rational decision-making (RDM) model, where decision-makers select the best alternative from the options evaluated in previous phases. Several theoretical frameworks aid in understanding how individuals and organizations make these choices. One of the foundational theories is Expected Utility Theory, which asserts that individuals make decisions by seeking to maximize their expected utility. This theory integrates preferences, probabilities, and potential outcomes into the decision-making process (Kahneman & Tversky, 2013; Bag et al., 2021). Another significant perspective is the Regret Theory, introduced in 1982. This theory suggests that individuals often make choices aimed at minimizing potential regret associated with their decisions, highlighting the emotional impact of decision outcomes (Loomes & Sugden, 1982; Bell, 1982).

Despite the focus on rational decision-making frameworks, researchers acknowledge the influence of emotions, especially during the Choice Phase. Emotion-based decision theories examine how feelings and emotional experiences affect preferences. For instance, Loewenstein and Lerner (2003) emphasize the role of affective states in shaping choices. Additionally, Thaler and Sunstein (2008) highlight how behavioral economics challenges the notion of perfect rationality by considering psychological biases, heuristics, and social influences on decision-making. By integrating these theories, the choice phase reflects the complexity of decision-making, illustrating that choices do not depend on rational computations but are also significantly shaped by emotional and psychological factors.

In summary, the choice phase of RDM is the culmination of the decision-making process, where individuals select the most appropriate alternative from the evaluated options. This phase builds upon the insights gained during the previous phases—intelligence gathering and analysis & design—ensuring that the chosen solution aligns with the established objectives and criteria. In this phase, decision-makers weigh the pros and cons of each alternative, often using techniques such as multi-criteria decision analysis or decision matrices to facilitate the comparison of options. It is essential to consider not only the quantitative data but also qualitative factors, such as stakeholder preferences and potential impacts. Once an alternative is selected, implementation strategies are developed to execute the decision effectively, accompanied by plans for monitoring and evaluating outcomes to ensure that the desired results are achieved. The choice phase emphasizes the importance of informed and deliberate decision-making, enabling individuals and organizations to navigate complexities and uncertainties in their environments confidently.

Trust

Trust in technology is a multifaceted construct that significantly influences user acceptance and the effectiveness of technological solutions. In the context of digital transformation, trust is frequently described as the expectation that a technology will perform reliably and meet its intended objectives (McKnight et al., 2002). This understanding emphasizes the importance of reliability and effectiveness in technology, as users must believe in a system's ability to deliver consistent outcomes. Trust in the digital transformation sector can be shaped by several factors, including user experience, system design, and the perceived credibility of information sources. For instance, a study conducted by Mayer et al. (1995) explores the dynamics of trust, highlighting its reliance on ability, benevolence, and integrity. In the realm of digital transformation, users often evaluate these factors to determine their trust in technology. Additionally, trust is critical for the adoption of new technologies, as indicated by research from Gefen et al. (2003), which illustrates that trust significantly influences user acceptance and continued use of technology. These insights underscore the multi-faceted nature of trust in technology, which is essential for fostering user confidence and promoting effective interactions with various systems. This concept is critical, especially in environments characterized by uncertainty and risk, such as online transactions and data privacy.

Several theoretical frameworks have been developed to understand trust in technology. The Technology Acceptance Model (TAM) highlights perceived usefulness and perceived ease of use as key factors that affect users' intentions to embrace technology (Davis et al., 1989). However, trust also plays a significant role in this model. Furthermore, the Integrative Trust Model emphasizes the role of trustworthiness, which encompasses competence, benevolence, and integrity, in shaping users' attitudes toward technology (Gefen, 2002).

Trust in technology, especially when it comes to machine learning, has become a crucial area of investigation as ML systems play increasingly significant roles in various aspects of society, ranging from healthcare to finance and beyond (Adadi & Berrada, 2018). In the realm of ML, trust involves users' confidence in the accuracy, fairness, transparency, and accountability of ML algorithms and systems. Several factors influence individuals' trust in ML technology. These include algorithmic transparency, interpretability, performance, user experience, and the presence of biases and uncertainties (Ferrario et al., 2020). Algorithmic transparency is crucial in understanding how machine learning (ML) algorithms arrive at their decisions. It refers to the degree to which users can comprehend the processes and logic behind algorithmic outcomes. This transparency is essential for fostering trust, accountability, and ethical usage of AI technologies (Doshi-Velez & Kim, 2017). Interpretability relates to the ability to explain and interpret ML models' outputs in a meaningful way. Performance measures the accuracy and reliability of ML systems, while user experience encompasses usability and satisfaction with ML applications. Biases and uncertainties in ML algorithms can undermine trust by leading to unfair or unpredictable outcomes (Araujo et al.,2020).

Despite efforts to enhance trust in ML technology, several challenges remain. These include the complexity of ML algorithms, the black-box nature of certain models, the trade-off between transparency and performance, and the dynamic nature of data and societal values. Many directions should be considered in future such as; focus on developing more transparent and interpretable ML models, mitigating biases and uncertainties, improving user understanding and engagement with ML technology, and addressing ethical and regulatory concerns (Ribeiro et al., 2016).

Furthermore, Trust is a crucial element in decision-making processes, impacting both individual and group dynamics. It can facilitate collaboration, reduce conflict, and enhance the efficiency of decision-making (Kahneman, 2011). Trust in decision-making is affected by multiple factors, including prior experiences, perceived credibility, and the context in which decisions are made (Mayer et al., 1995). In the realm of organizational decision-making, trust can mitigate the negative effects of uncertainty and complexity. Members within the team trust each other; they are more likely to share information openly, engage in constructive dialogue, and support collective decision-making (Liu, 2021).

In the context of digital transformation in e-government, Trust refers to citizens' confidence in governmental online services and their ability to deliver on promises regarding transparency, security, and service quality (Satti & Rasool, 2024). The notion is essential for the effective execution and acceptance of e-government initiatives. It is essential in ensuring that these initiatives are embraced by users and stakeholders alike, as trust influences citizens' willingness to engage with digital services (Abu-Shanab, 2014). The E-government trust model incorporates various dimensions of trust, including institutional trust (trust in the government as an institution), interpersonal trust (trust in individuals within the government), and technological trust (trust in the technology used in e-government services). Additionally, factors such as the perceived quality of information, the reliability of services, and the protection of personal data play significant roles in shaping trust in e-government (Belanger & Carter, 2008).

Trust in ML technology is essential for its successful adoption and widespread use in various domains. By understanding the factors influencing trust, implementing trust-building mechanisms, and addressing existing challenges, researchers and practitioners can work towards creating more trustworthy and beneficial ML systems.

Jordanian e-Government

The digital transformation in the governmental sector offers significant opportunities to enhance government efficiency, increase transparency, and boost citizen engagement. By understanding the drivers, challenges, and future directions of digital transformation in e-government, policymakers, researchers, and practitioners can work towards realizing this potential and building more inclusive and responsive governments. Machine learning (ML) has become a game-changing technology with the capacity to revolutionize numerous sectors, including e-government. In Jordan, the adoption of ML in e-government initiatives holds promise for enhancing service delivery, improving decision-making processes, and fostering citizen engagement (Al-Nawasrah et al., 2020).

The implementation of ML in Jordanian e-government is still in its nascent stages, with several initiatives and pilot projects underway across different government institutes. These initiatives concentrate on areas such as image recognition, natural language processing, and data analytics. For instance, government institutes utilize ML algorithms to process large datasets, uncover insights, detect patterns, and make better-informed decisions. Additionally, NLP techniques are employed to enhance the efficiency of citizen services by automating text analysis and response generation in customer support systems (Qasem et al., 2021).

Although ML integration in Jordanian e-government offers promising benefits, it also encounters various challenges. These include limited technical expertise and resources, data privacy and security concerns, interoperability issues, and organizational barriers within government agencies. Addressing these challenges requires concerted efforts from government stakeholders, academia, and the private sector to build capacity, establish data governance frameworks, and foster collaboration (Alomari et al., 2018, Qasem et al., 2021).

Furthermore, there are significant opportunities for the expansion and integration of ML in Jordanian e-government. Key areas for future development include the deployment of ML-powered chatbots for citizen interaction and support, the automation of administrative processes through predictive analytics and recommendation systems, and the enhancement of cybersecurity measures through ML-based threat detection and prevention. Moreover, there is potential for collaboration with international partners and leveraging emerging technologies such as block chain, data mining, and the Internet of Things (IoT) to further strengthen the capabilities of ML in e-government applications.

In conclusion, the adoption of ML in Jordanian e-government holds promise for improving service delivery, enhancing decision-making processes, and increasing citizen engagement. By addressing existing challenges and seizing future opportunities, Jordan can leverage ML to advance its e-government agenda and create more efficient, transparent, and responsive governance systems.

Related Research and Hypothesis Development

The following literature review presents a chronological analysis of significant research contributions in machine learning and rational decision-making domains. By examining selected articles, this review covers a broad spectrum of topics, including the historical context of AI, various applications of machine learning, and enhancing decision support systems. It also delves into classification frameworks, the representation of racial categories in machine learning, and the influence of AI on e-government initiatives. Moreover, this review investigates the intricate relationship between trust and RDM within AI, highlighting the evolving dynamics of human-AI interactions. Understanding these interconnections is crucial as they reflect the complexities and challenges faced in integrating ML technologies into RDM processes.

Lantz (2021) discussed the historical context of AI and ML and justified the investment in AI, even in industries where data is not the core business function. It demystified the means by which computers learn and presented various algorithms and evaluation methods used in machine learning. The article emphasizes the importance of understanding the balance between bias, variance, and model complexity in machine learning. Kureljusic and Metz (2023) concentrated on using ML in accounts receivables management, highlighting the essential importance of data integrity and model verification. Their study explored the expected advantages of employing ML algorithms in credit risk assessment, collection prioritization, and customer segmentation. They underscored the necessity of ensuring data quality and availability and the importance of proper model validation and interpretation in the context of machine learning applications in accounts receivables management.

While both articles address the use of ML algorithms, which are treated as independent variables in our study, Lantz offers a broader perspective on machine learning in general. In contrast, Kureljusic and Metz provide a more focused examination of the specific application of ML within accounts receivable management.

Alexopoulos et al. (2019) investigated the influence of using ML on e-government, examining how these technologies can enhance public services and improve decision-making processes within governmental frameworks. The authors discussed how machine learning techniques are being applied in electronic government services to improve service delivery, decision making, and citizen engagement. The paper highlighted various machine learning applications in e-government, such as predictive analytics for resource allocation, sentiment analysis for citizen feedback, and natural language processing for chatbots and virtual assistants. The study also addresses the limitations and considerations relevant to adopting ML in e-government, including data privacy, algorithmic bias, and transparency. Their study underscores the transformative potential of ML in automating tasks, analyzing large datasets, and facilitating more efficient interactions between government agencies and citizens. By examining different machine learning applications within the e-government framework, the authors offer valuable insights into the opportunities and challenges of incorporating these advanced technologies into public administration. The paper's results enhance the understanding of the possible advantages and consequences of machine learning in transforming e-government practices.

Power et al. (2019) stressed the significance of utilizing data-driven analytics and evidence-based methods to minimize bias and enhance decision-making. The authors discuss various types of biases that can influence decision making, such as confirmation bias, availability bias, and anchoring bias. They highlight the need for organizations to be mindful of these biases and implement strategies to mitigate their influence on processes of decision-making. The researchers also explored the role of analytics in decision-making, including applying statistical models, data visualization, and predictive analytics. This study argued that by leveraging analytics and evidence, decision-makers can make more informed and rational decisions. In this study, after establishing a foundation through literature review and understanding of the research problem, we developed a primary hypothesis (H1) to guide the investigation as below:

H1: A significant positive influence of supervised machine learning on rational decision making.

However, because the RDM involve multiple dimensions and specific aspects that need exploration, we further divided H1 into three sub-hypotheses. By creating sub-hypotheses, we can analyze the primary hypothesis (H1) in a more detailed and nuanced way. Each sub-hypothesis tests a different phase within the RDM as below:

H1a**:** A significant positive influence of supervised machine learning on the intelligence gathering phase of rational decision making.

H1b: A significant positive influence of supervised machine learning on the analysis and design phase of rational decision making.

H1c: A significant positive influence of supervised machine learning on the choice phase of rational decision making.

Both researches performed by Merkert et al. (2015) and Wang et al. (2018) investigated ML algorithms. Wang et al. focused on unsupervised feature learning, introducing an innovative anomaly detection framework designed to enhance decision support, which aligns with the demand for effective decision-making tools in digital transformation. Meanwhile, Merkert et al. examined the application of ML in decision support systems, emphasized both the advantages and drawbacks of integrating ML into decision support systems, highlighting issues such as data quality, interpretability, and scalability. Their survey contributes to understanding decision-making processes and lays the groundwork for evaluating the impact of machine learning in e-government within our study. Additionally, the survey features real-world case studies and examples that illustrate the effectiveness of utilizing ML in supporting decisions. While each study examines the application of ML in supporting decisions, they differ in focus: Merkert et al. provide a comprehensive survey that enhances the understanding of ML's role in supporting decision systems, whereas Wang et al. propose a novel framework that advances the field of anomaly detection and offers insights for developing more robust and accurate decision support systems.

Dasgupta and Nath (2016) introduced the classification framework categorizes machine learning algorithms based on their characteristics and functionalities. Their classification framework establishes a foundation for comprehending the various categories of ML algorithms relevant to digital transformation. This framework serves as a valuable resource for decision-makers in the framework of e-government, facilitating their understanding of how different machine learning algorithms can be applied effectively. By clarifying the distinctions among these algorithms, the framework enhances the capacity of stakeholders to make informed decisions regarding the integration of machine learning technologies. Alloghani et al. (2020) performed a comprehensive review that examined machine learning algorithms (SML and UNSML) within the realm of data science, highlighting their strengths, limitations, and potential uses. This thorough review aids in choosing suitable algorithms for specific tasks within the e-government sector, providing valuable insights to inform decision-making processes. The authors discussed fundamental concepts and principles underlying supervised and unsupervised learning, establishing a solid foundation for understanding these algorithms and their practical implications. The study examines the performance and effectiveness of the algorithms according to different criteria, such as accuracy, scalability, interpretability, and computational efficiency. The authors identified gaps and areas for upcoming research in the field of ML algorithms for data science in supporting decision-making. Where our research focuses on this point and expands the study of the effect of machine learning algorithms, especially in a systematic way for rational decision-making.

Theses literature lead to formulation of H2 and its sub-hypotheses allows us to break down the second research question into specific, testable components. Hypothesis H2 presents a general expectation about the relationship that we are investigating between UNSML and RDM. However, this relationship may involve several underlying phases of RDM that need to be examined individually. Therefore, by establishing sub-hypotheses, we are able to dissect H2 into smaller, focused questions that address specific elements within the second main hypothesis as below:

H2: A significant positive influence of unsupervised machine learning on rational decision making.

H2a**:** A significant positive influence of unsupervised machine learning on the intelligence gathering phase of rational decision making.

H2b: A significant positive influence of unsupervised machine learning on the analysis and design phase of rational decision making.

H2c: A significant positive influence of unsupervised machine learning on the choice phase of rational decision making.

Ryan, 2020 addresses the ethical considerations in AI; this article emphasizes the significance of reliability, transparency, and public trust, which is similar to our research mediating variable (trust). The author's stress on the importance of trust in AI systems resonates with the need for reliable and trustworthy AI tools, which is crucial in e-government decision-making. Similar to Ferrario et al. (2020) proposed a multi-layer model of trust to examine the interactions between humans and artificial intelligence (AI). The model suggested that trust in AI is developed incrementally, with different layers of trust being built over time. The author discussed the significance of transparency, explainability, and accountability in fostering trust in AI systems. Both Ryan and Ferrario et al. studies contributed to understanding trust but differ in their specific focus.

In a related study, Araujo et al. (2020) examined general perceptions of automated decisions driven by AI, focusing on the causes that impact trust in AI systems that affect individuals' lives. The authors identified key elements that impact trust, including transparency, explainability, accountability, and perceived fairness in AI decision-making processes. They also discussed the implications of public trust for the adoption and acceptance of AI systems through different industries, including healthcare, finance, and criminal justice. However, their research does not address the government sector, presenting an opportunity for future studies to fill this gap. The insights from their findings highlight the importance of addressing public concerns, and promoting transparency and accountability in decision-making processes driven by AI.

This leads to a third main hypothesis, H3, assumes a general positive influence of ML on trust, inspired by literature that shows users are likely to trust systems that are transparent, accurate, and reliable. For both ML divisions SML and UNSML as below:

H3: A significant positive influence of machine learning on trust.

H3a**:** A significant positive influence of supervised machine learning on trust.

H3b: A significant positive influence of unsupervised machine learning on trust.

Janssen et al. (2022) introduced a framework of decision-making applied in e-government that leverages ML techniques to enhance the decision-making process. The framework includes several steps such as problem identification, data collection, model development, and decision-making. The authors centered on data governance, where they explored the challenges and strategies associated with organizing data for trustworthy AI, focusing on quality, integrity, and ethical use.

Cao et al. (2021) investigated managers' attitudes and behavioral intentions of the implementation of AI techniques for decision-making in organizations. Their objective was to identify the factors influencing managers' acceptance and adoption of AI. To gather data, the authors conducted a survey among managers across various industries, employing statistical analysis methods similar to those used in our research. Their findings highlighted the essential role of trust in AI systems, aligning with our study's focus on trust as a mediating variable. They also emphasized the necessity for organizations to provide training and support to improve managers' skills and understanding of AI. Similar to our research context of digital transformation in e-government. Thus, we propose H4 to test how trust significantly impacts RDM in a specific context of digital transformation.

H4: A significant positive influence of trust on rational decision making.

H4a: A significant positive influence of trust on the intelligence gathering phase of rational decision making.

H4b: A significant positive influence of trust on the analysis and design phase of rational decision making.

H4c: A significant positive influence of trust on the choice phase of rational decision making.

Bag et al. (2021) introduced AI framework designed for business-to-business marketing decision-making. This research employs AI technologies to promote knowledge creation and improve overall organizational performance. The study focused on improving firm performance through the application of AI techniques in the business-to-business marketing context. Even though it is a different context than our research, where our focus is on the government sector, the authors propose an integrated framework that leverages ML to facilitate knowledge creation and support rational decision-making in business-to-business marketing, which is the same concept that our research tries to focus on. The framework proposed by Bag et al. aimed to enhance the understanding of customer needs, preferences, and behavior, enabling firms to make informed marketing decisions.

Compared to Ingrams et al. (2022), we found that their study is more relevant because it evaluated citizen perceptions of using AI techniques in government decisions. The research focused on the trust that citizens have in AI systems used by the government. The study found that citizens have mixed perceptions of AI in government decision making, with some expressing trust and others expressing concerns. Factors such as trust factor play a role in shaping citizens' trust in AI systems.

Fifth hypothesis is formulated in response to a gap in the literature, aiming to investigate this emerging aspect of mediating role of trust in study min relationship between ML and RDM. Thus we hypothesized the fifth hypothesis and sub hypotheses as below:

H5: A mediation influence of trust within the relationship between machine learning and rational decision making.

H5a: A mediation influence of trust within the relationship between supervised machine learning and rational decision making.

H5b: A mediation influence of trust within the relationship between unsupervised machine learning and rational decision making.

This comprehensive review of literature offers a detailed insight into the development of ML (SML and UNSML), and their intersection with decision-making processes. From foundational works that classify algorithms and propose anomaly detection frameworks to recent studies exploring public perception, trust, and ethical considerations, the literature underscores the multifaceted nature of AI applications and taking into account the expected impact of trust on RDM.

Research Model

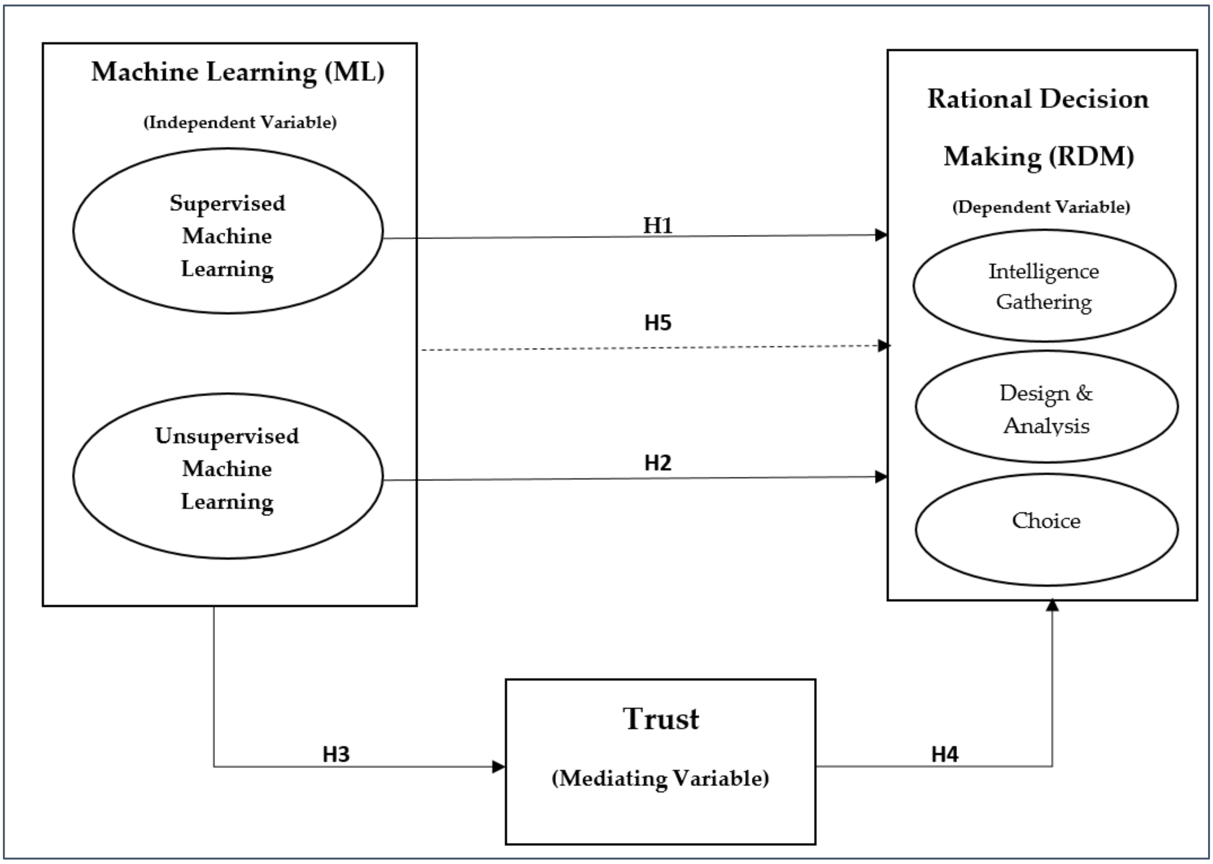
The research model illustrates in figure1 the relation between the independent variable, machine learning (ML)**,** the dependent variable, rational decision-making (RDM), and the mediating variable, trust. It conceptualizes ML as the independent variable, divided into SML and UNSML, both hypothesized to influence RDM (H1, H2) directly. Trust is positioned as a mediating variable, bridging the impact of ML on RDM. The model suggests that ML affects trust (H3), which in turn influences rational decision-making (H4), with a final (H5) proposing that trust mediating the relationship between ML and RDM.

Rational decision making as dependent variable is broken down into three phases: intelligence gathering, analysis & design**,** and choice, emphasizing the significance of trust in enhancing RDM process through the integration of ML technologies.

The framework integrates both machine learning approaches with trust as a central factor influencing how these technologies affect the phases of rational decision-making. This highlights trust as a critical element in ensuring the effective use of ML in RDM processes.

Figure 1

Conceptual framework of study



Summary of Hypothesis

H1: A significant positive influence of supervised machine learning on rational decision making.
H1a**:** A significant positive influence of supervised machine learning on the intelligence gathering phase of rational decision making.
H1b: A significant positive influence of supervised machine learning on the analysis and design phase of rational decision making.
H1c: A significant positive influence of supervised machine learning on the choice phase of rational decision making.
H2: A significant positive influence of unsupervised machine learning on rational decision making.
H2a**:** A significant positive influence of unsupervised machine learning on the intelligence gathering phase of rational decision making.
H2b: A significant positive influence of unsupervised machine learning on the analysis and design phase of rational decision making.
H2c: A significant positive influence of unsupervised machine learning on the choice phase of rational decision making.
H3: A significant positive influence of machine learning on trust.
H3a**:** A significant positive influence of supervised machine learning on trust.
H3b: A significant positive influence of unsupervised machine learning on trust.
H4: A significant positive influence of trust on rational decision making.
H4a: A significant positive influence of trust on the intelligence gathering phase of rational decision making.
H4b: A significant positive influence of trust on the analysis and design phase of rational decision making.
H4c: A significant positive influence of trust on the choice phase of rational decision making.
H5: A mediation influence of trust within the relationship between machine learning and rational decision making.
H5a: A mediation influence of trust within the relationship between supervised machine learning and rational decision making.
H5b: A mediation influence of trust within the relationship between unsupervised machine learning and rational decision making.

Moving forward, future research should continue to address emerging challenges, including bias, transparency, and accountability, while exploring innovative applications and frameworks that foster responsible AI development and deployment.

The review of existing literature presents a comprehensive chronological examination of key research contributions in the fields of AI, ML, and RDM. The selected articles cover diverse topics such as the historical context of AI, machine learning applications, decision support systems, racial categories ML, and the impact of AI on e-government. Additionally, the review delves into the interaction between trust, ethics, and decision-making in AI, shedding light on the evolving landscape of human-AI interactions.

Summary

The literature review establishes a theoretical basis by examining key themes of machine learning (ML), rational decision-making (RDM), trust, and digital transformation (DT) within the e-government context. It emphasizes ML's role in processing large datasets, offering insights that aid government decision-makers in making more data-driven, rational choices. Trust is identified as a crucial mediator between ML and RDM, as government officials are more likely to rely on ML-driven insights when the technology is perceived as transparent, accurate, and reliable. Digital transformation further accelerates the integration of ML into government processes, enhancing decision-making efficiency and service delivery while highlighting the need for a supportive organizational culture.

The review also highlights critical research gaps, including limited exploration of ML’s specific role in government decision-making and a lack of empirical studies on the factors that influence trust in ML within government settings. There is a recognized need to examine how aspects like transparency and user control impact trust in ML among government officials, as well as how digital transformation affects both trust and decision-making processes. These identified gaps suggest that further research is needed to fully understand the potential and limitations of ML in government, offering direction for studies that could provide actionable insights for public sector technology adoption.

CHAPTER III
RESEARCH METHODOLOGY

Methodology

The research design, participants, population, and sample are outlined in this chapter. Followed by the procedures for data collection and analysis, as well as the methods used to interpret the findings. Also, it presents the research methodology employed to examine the influence of using ML techniques on RDM throughout the digital transformation of government electronic services in Jordan. A quantitative approach is adopted to reach the research goals, detailing the study sample, data collection methods, procedures, instruments, and the validity and reliability of techniques used to obtain results. The methodology utilizes a hypothesis-driven method, concentrating on quantitative research to tackle layout, measurement, and sampling challenges, supported by a detailed plan for data collection, processing, and analysis. The researcher implemented structured quantitative methods, assuring that all processes were carefully organized in advance of data collection. Data processing and analysis were carried out using statistical methods, tables, and figures, with a focus on linking the results to the hypotheses.

Research Design

The researcher details the methodology employed in this study to evaluate the influence of using ML techniques on enhancing the RDM process within digital transformation efforts. This research outlines the procedures used to investigate data and examine the hypotheses by gathering data, quantifying the variables in the research conceptual framework, and employing various analytical tools, including SPSS v25 and AMOS v23. Prior to conducting the research, several key factors were considered, for example, the nature of the research, the justification of the research, and the methods used for data collection. This process involved developing an idea, concept, or theory, and then creating a scale to empirically assess it (Creswell, 2009).

The researcher employed a descriptive-analytical approach in the study design, which helps provide a clear insight into the phenomenon under examination and defines the nature of the interactions between its variables within the context of Jordan's e-government. The research also involves the use of a field method to collect primary data through a questionnaire, which the researcher developed based on previous studies and relevant literature.

Statistical analysis was carried out to respond to the study's questions and assess the validity of its hypotheses. Additionally, a desktop and electronic survey was conducted to leverage references and available sources to construct the theoretical framework. This allowed the researcher to connect the current study's findings with those of previous studies on the same topic, providing a comprehensive scientific explanation of the phenomenon or problem. Based on these findings, the researcher presented several recommendations.

Participants / Population / Sample / Study Group

The main goal in designing the study sample was to develop a thorough and accurate representation of e-government employees in Jordan, specifically targeting those at the middle management level. The reasoning behind this focus is that middle-level managers perform a variety of tasks across different departments using machine learning technology and are more involved in day-to-day decision-making, which tends to be more rational. In contrast, upper management typically deals with strategic decisions. To ensure the validity and generalizability of the results, targeting middle-level management was considered appropriate.

The next step involved obtaining approval from the Ethics Committee at Near East University (NEU). Once the approval was secured, the questionnaire was distributed electronically between October 2023 and December 2023 to employees across various departments within the Ministry of Digital Economy and Entrepreneurship (MoDEE). As the key agency responsible for e-government initiatives in Jordan, MoDEE plays a central role in overseeing the adoption and implementation of new technologies within the government. Serving as the technical support unit of the Jordanian government, MoDEE ensures that technological innovations are effectively integrated into public services to enhance efficiency and digital transformation.

After gathering the responses, they were input into a database for analysis. The study's target population comprised middle-level administrative employees at MoDEE, who were selected purposefully due to their involvement in tasks that utilize ML technology. This level of management was specifically chosen because these employees are likely to make more rational decisions in their daily operations.

The focus was on employees within the digital transformation directorate, who are experienced in applying ML techniques in decision-making processes. They play a crucial role in executing Jordan's AI strategy for 2023–2027, which includes a range of projects aimed at enhancing RDM through ML. This study offers a unique contribution by examining the role of ML and trust in RDM within the Jordanian government, an area that has not been explored in the region previously.

According to internal reports from MoDEE generated in 2023 by the Human Resources division, the total number of targeted employees was 245. This figure represents the specific group of employees identified for inclusion in the research being referenced. These internal reports provide official data that guided the sampling and analysis process within the study. To ascertain the optimal sample size for this study, a formula suggested by Sekaran and Bougie (2016) was employed. This formula, tailored for finite populations, optimizes the sample size by balancing the requirement for statistical confidence with practical aspects of data collection, considering factors such as time, cost, and potential non-responses while achieving a 95% confidence level and a 5% margin of error. The formula is:

$$n= N\times Z^2\times p\times q \, / \, e^2\times(N-1) +Z^2\times p\times q$$

(n = Sample size, N = Population size, Z = Z-value (based on the desired confidence level e.g., 1.96 for 95%, p = Estimated proportion of the population that has the attribute of interest, q = 1 – p (proportion without the attribute), e = Margin of error).

A confidence interval is a range of values calculated from sample data that provides an estimate of where the true population parameter (such as the population mean or proportion) is likely to fall. It is expressed with a specific level of confidence, usually 95% or 99%, which represents the probability that the interval contains the true value. A confidence level of 95% with a 5% margin of error is generally preferred for studies in the fields of social sciences research and business studies (Lu et al., 2018; Sekaran & Bougie, 2016).

In this research, with a total population of 245 individuals, a sample size of 152 was determined to be sufficient to achieve a 5% margin of error (precision level) at a 95% confidence level. This calculation was based on the population size and the formula mentioned above. A convenience sampling method was employed, meaning data was collected from participants who were easily accessible and willing to participate, rather than selecting a random or stratified sample.

Data Collection Tools/Materials

Study Variables and Instrument

The questionnaire is divided into four sections, comprising 46 items: the ML Scale, RDM Scale, and the Trust Scale, with a special section for demographic information. Cronbach's alpha values for each of these scales are summarized in table 6, indicating their reliability.

Questionnaire Translation

To ensure that the research instrument was accurate and culturally appropriate for Arabic-speaking participants, the study employed a translation and back-translation process. Since the final sample was composed of Arabic-speaking, non-English users, it was necessary to translate the original English statements into Arabic. This translation allowed participants to fully understand the survey items in their native language, reducing potential misinterpretations due to language differences. To verify the accuracy of this translation, a back-translation was conducted, meaning the Arabic version was independently translated back into English. This process allowed the researchers to compare the back-translated version to the original English statements and check for consistency. This approach was further validated by piloting the translated instrument with a small group of Arabic-speaking users. This pilot group allowed the researchers to identify potential issues in understanding, cultural relevance, or wording before distributing the survey to the full sample.

Rational Decision-making (RDM) (Dependent variable).

The dependent variable, RDM, consists of (10) items distributed into three sub-dimensions as follows in table 1. The RDM used in this study was developed mixing between multi researchers' scales by Scott, and Bruce (1995), Spicer, and Sadler-Smith (2005), Bokhari, & Myeong, S. (2022) this scale consists of 10 items with the format of a typical Five-Point Likert Scale ranging from 1: Strongly Disagree to 5: Strongly Agree, with overall a Cronbach's alpha score of 0.875. According to Hair et al. (2014), a Cronbach's alpha value of 0.7 or higher is considered necessary to establish the reliability of a measurement scale and ensure the study's acceptability. In this research, Cronbach's alpha scores for the RDM variables met or exceeded this threshold, indicating that the measurements used in the study are reliable. This means that the items within each RDM variable are internally consistent, and the responses are likely to be dependable for further analysis.

Table 1.

Distribution of sub-dimensions of the dependent variable

Sub-dimensions	No of Items	Sequence Numbers
Intelligence gathering	4	1,2,3,7
Analysis and Design	3	4,5,6
Choice phase	3	8,9,10

Machine Learning (ML) (Independent variable).

The independent variable (Machine Learning) consists of (30) items distributed into two sub-dimensions, as follows in table 2. The ML used in this study was developed by mixing between multi researcher scales (Bokhari, & Myeong, 2022; Ongena et al., 2020) scale contains 30 items with the format of a typical Five-Point Likert Scale ranging from 1: Strongly Disagree to 5: Strongly Agree which divided into two sub-dimensions: SML and UNSML with overall value of a Cronbach's alpha equal of 0.958. As a result, the Cronbach's alpha scores for the ML variables in this study suggest that the measurements are reliable.

Table 2.

Distribution of sub-dimensions of the Independent variable

Sub-dimensions	No of Items	Sequence Numbers
Supervised Learning	15	11-25
Unsupervised Learning	15	26-40

Trust (Mediating Variable)

The mediating variable(Trust), consists of six items, as outlined in Table 3. Abu-Shanab (2014) developed the trust scale, which consists of six items formatted on a standard Five-Point Likert Scale. The scale demonstrated a Cronbach's alpha score of 0.817, indicating good reliability. Consequently, Cronbach's alpha scores for the trust variables in this study indicate that the measurements are reliable. With values meeting or exceeding the accepted threshold of 0.7, the internal consistency of the trust-related items is confirmed, ensuring that the responses are consistent and dependable. This reliability supports the validity of the conclusions drawn from the data regarding trust in the study context.

Table 3.

Distribution of the dimension of the mediating variable

Dimensions	No of Items	Sequence Numbers
Trust	6	41-46

Data Collection Procedures

To gather credible and reliable data, a questionnaire was designed based on a comprehensive review of relevant literature to effectively test the research hypotheses. The questionnaire served as a structured, standardized tool that ensured consistent data collection and was chosen as the most appropriate method to address the research objectives. To improve the clarity and effectiveness of the questionnaire, two consecutive pre-testing rounds were conducted. First, the questionnaire was reviewed by subject matter experts, who provided feedback on the clarity, relevance, and structure of the questions. This feedback informed necessary adjustments to ensure the items accurately aligned with the study's aims. In the second round, a pilot test was conducted with a small sample of individuals resembling the target audience. This step verified the clarity and comprehensibility of each item, further refining the wording and organization to optimize the questionnaire's effectiveness in capturing the required information.

Participants were informed that their involvement was entirely voluntary, with no obligation to participate. This assurance minimized the risk of coercion and encouraged participants to respond genuinely, supporting the validity and reliability of the data collected. The purpose of the research was clearly outlined at the start of the questionnaire, and verbal consent was obtained from each participant before distributing the survey (see Appendix A for details).

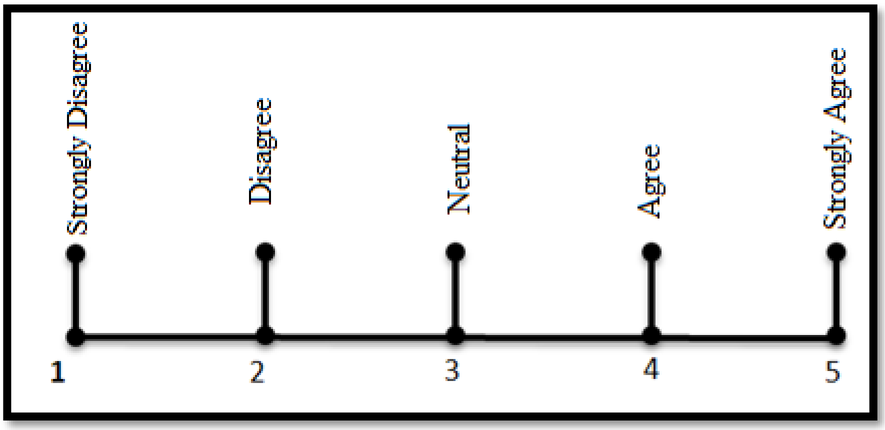
Data collection targeted middle-level management professionals across various departments within the Ministry of Digital Economy and Entrepreneurship (MoDEE) who were either involved in or open to the adoption of machine learning. Before data collection began in October 2023, MoDEE organized multiple workshops for all employees, aimed at introducing the basics and potential applications of machine learning within government services. These workshops provided employees with foundational knowledge on machine learning, fostering awareness and preparing them for its potential integration within their roles.

Following the workshops, the questionnaire was distributed electronically via email and employee email groups between October and December 2023. This distribution method ensured broad accessibility and convenience, allowing participants to respond at their own pace. Utilizing this structured and remote approach also supported consistency across responses and provided an efficient means of gathering insights from a large number of relevant participants. The workshops, paired with the electronic distribution of the questionnaire, created an informed respondent base, enhancing the quality and relevance of the data collected.

The study utilized a five-point Likert scale to categorize participants' responses based on their levels of agreement, as illustrated in figure 2. This scale ranges from strong agreement at one end to strong disagreement at the other, with three intermediate levels of agreement in between. Each point on the scale is assigned a numerical score, with a score of 1 representing the lowest level of agreement (strong disagreement) and a score of 5 representing the highest level (strong agreement). This format allowed respondents to express varying degrees of agreement or disagreement with the statements presented, facilitating a nuanced analysis of their attitudes and perceptions. This scoring system applies consistently across all five response options (Kothari, 2013).

Figure 2

Five-point Likert scale



Data Analysis Plan

In this research, SPSS v25 and AMOS v23 were used to conduct data analysis, examine the gathered sample and test suggested hypotheses. The analysis will primarily utilize multiple regression techniques, acknowledged as a contemporary and efficient substitute for conventional analysis techniques. Multiple regression analysis in SPSS offers enhancements such as confirmatory analysis, exploration of non-linear effects, and evaluation of mediating influences, making it well-suited for our research objectives. Multiple regression is widely endorsed by scholars in the field for exploring mediation effects, utilizing both primary and secondary data. Given the nature of our research and its alignment with prior studies on mediation effects in decision-making, we determined that employing multiple regression analysis with SPSS would be the most appropriate method for our investigation. To develop a measurement model for the self-rating scales, we will perform:

Confirmatory Factor Analysis (CFA) alongside a convergent validity test will allow us to verify that our scales accurately measure the intended constructs. CFA Implementation: We will conduct CFA to confirm the factor structure of the self-rating scales and ensure that the observed variables align with the underlying constructs.

Modification Index Utilization: During the CFA process, we will use the modification index to identify variables for refinement. We will prioritize the removal of components with the highest modification index values to enhance the model's fit, continuing this process until we achieve the desired goodness of fit.

Goodness-of-Fit Evaluation: While most goodness-of-fit indicators are expected to exceed the specified thresholds, we will closely monitor factor loadings. Any observed variable components that fall below 0.5 will be eliminated to maintain the validity of our data framework.

Validation of Observed Variables: Ultimately, we will ensure that all observed variable components demonstrate factor loadings exceeding the critical threshold of 0.5, which will confirm their validity and reinforce the robustness of our measurement model.

This comprehensive data analysis plan will enable a thorough examination of our hypotheses and enhance the reliability and validity of our findings within the framework of RDM and ML. By systematically applying various analytical techniques, we can rigorously assess the relationships and patterns in the data, thereby ensuring that our conclusions are well-supported and applicable to the broader context of the study. This structured approach will contribute to a deeper understanding of the impact of ML on RDM processes.

Summary

This chapter outlines the research methodology used to evaluate the impact of ML on RDM during Jordan’s digital transformation. A quantitative approach is adopted, employing structured questionnaires distributed to employees in Jordan's Ministry of Digital Economy and Entrepreneurship (MoDEE). The methodology involves hypothesis-driven research supported by data collection, processing, and analysis using statistical tools such as SPSS and AMOS.

CHAPTER IV

Findings and Discussion

This chapter presents the findings from our study, which explores the relationships between ML, trust, and RDM among middle-level management professionals in MoDEE. We begin by providing a comprehensive analysis of the collected data, which includes descriptive statistics and inferential analyses designed to address our research hypotheses. The results are systematically organized to emphasize key patterns and insights that emerged from the quantitative analysis, particularly highlighting the mediating role of trust in the RDM process.

Descriptive Statistics

This research seeks to evaluate the influences of using ML on RDM during DT implementation in e-government. To achieve this objective, the researcher distributed a total of 163 questionnaires were collected, of which 141 were deemed valid for statistical analysis. This resulted in a response rate of 86.5%. The high validity rate of the responses indicates a strong engagement from participants and enhances the robustness of the findings derived from the analysis. Following the collection of responses, the questionnaire, which consists of 46 items, was converted into a quantitative scale by assigning numerical values to the response categories. The overall scores from respondents for each item were classified, as demonstrated in table 4. his categorization allows for a clearer understanding of the distribution of responses and helps identify patterns or trends within the data. By organizing the scores, we can effectively analyze the overall sentiment and assess how different items relate to the constructs being measured.

Table 4.

Degree of approval of the questionnaire paragraphs

Likert-Scale	Categorization	Description
5	4.2 – 5	Strongly Agree
4	3.4 – 4.19	Agree
3	2.6 – 3.39	Neither
2	1.8 – 2.59	Disagree
1	1 – 1.79	Strongly Disagree

The researcher assessed the questionnaire items based on the criteria outlined in table 4. According to these guidelines, the approval levels for each item are defined.

Distribution of Demographics Profile

The demographic characteristics of the respondents in this research were captured across four key aspects: gender, age, educational level, and years of experience. An overview of these demographic characteristics is presented in table 5. The data from the target population reflects a diverse range of age groups, with the highest percentage (38.3%) found in the 35-44 years' category, while the lowest percentage (2.8%) was recorded in the 55-64 years' category. Notably, the majority of respondents were in the 24-44 years' age group, which shows that the surge of young professionals gravitating towards middle-level management positions in the technology sector can be attributed to several factors that are relevant to the nature they are growing up in the digital age.

The educational level of the respondents was categorized into four groups, as detailed in table 5. Within the target population, the highest percentage (66.0%) was found among individuals holding a Bachelor's degree, while the lowest percentage (1.4%) was recorded for those with an Associate degree, as the minimum requirement for enrolment in government in recent years became having a bachelor's degree.

The percentage for Experience years' respondents reached (36.2%) for the Experience category (16 years and above), but the lowest percentage reached (12.8%) for Experience categories (0-3 years) which can be explained as young professionals in technology positions often accumulate a considerable amount of experience in the initial phase of their careers due to the high demand for their skills and the trend of early enrolment in tech jobs.

The gender was categorized as male and female for the respondents. Among the target population, males comprised 54.6% of the respondents, while females accounted for 45.4%. This distribution aligns with the traditional social dynamics in Jordan, where men often assume the primary role of breadwinners, while women typically engage in familial responsibilities.

However, recently, there has been a notable growth in female participation and involvement in technology roles, challenging and reshaping the traditionally male-dominated landscape. Females are breaking barriers and entering diverse roles within the tech industry, from software development and data analysis to cybersecurity and artificial intelligence.

Table 5.

Demographics of the study sample

Variable		Frequency	%
Age (Years)	18-24	6	4.3
	25-34	44	31.2
	35-44	54	38.3
	45-54	33	23.4
	55-64	4	2.8
	65- and above	-	-
	Total	141	100.0
Education (Degree)	Associate degree	2	1.4
	Bachelor	93	66.0
	Master	32	22.7
	Doctorate	14	9.9
	Total	141	100.0
Experience period (years)	0-3	18	12.8
	4-7	25	17.7
	8-11	21	14.9
	12-15	26	18.4
	16 and above	51	36.2
	Total	141	100.0
Gender	Male	77	54.6
	Female	64	45.4
	Total	141	100.0

Reliability, Correlation Coefficients, Model Validity, and Goodness-of-fit

After gathering the data, the researcher utilized SPSS v.25 software for analysis, following these steps: using Cronbach’s alpha coefficient, the validity and reliability of the questionnaire were initially evaluated. According to Sekaran and Bougie (2016), a Cronbach’s alpha value surpassing 0.70 indicates strong internal consistency among the measured variables, thus enhancing the reliability of the instrument. To further assess the stability of the study tool, the researcher applied Cronbach's internal consistency measure, a widely recognized method for evaluating reliability by examining the homogeneity of the items. This approach determines how well individual items correlate with one another and contribute to the overall scale. The findings of the reliability analysis outlined in table 6 indicate that Cronbach's alpha coefficients for the various dimensions and fields of the study ranged between 0.730 and 0.962. These values demonstrate a strong level of reliability, affirming that the instrument is suitable for practical use.

Table 6.

Reliability coefficients (Cronbach alpha)

Dimensions	Sub-dimensions	No of Items	Cronbach alpha
RDM	Intelligence gathering	4	0.730
	Analysis and Design	3	0.883
	Choice phase	3	0.848
	Overall (RDM)	**10**	**0.875**
ML	SML	15	0.910
	UNSML	15	0.962
	Overall (ML)	**30**	**0.958**
	Trust	**6**	**0.817**
	Total	**46**	**0.972**

The correlation analysis indicated positive relationships between the variables, with the correlation coefficients summarized in table 7. This table illustrates the strength of these relationships, categorizing them into scales ranging from negligible to very high correlations. The findings demonstrate that as one variable increases, so does the other, highlighting the interconnectedness of the measured constructs in the study.

Then, a detailed factor analysis was performed to determine the principal components underlying the data. This method was used to assess whether the factors included in the research effectively capture and represent the variables they are intended to measure. The analysis examined the relationships between the factors and the variables to determine the strength and clarity of these associations, ensuring that the selected factors were not only relevant but also provided meaningful insights into the constructs being studied. Through this process, the researcher could confirm that the factors were aligned with the theoretical framework and adequately explained the variance in the data.

As described by Hair et al. (2014), Exploratory Factor Analysis (EFA) is utilized to analyze data and determine the optimal number of factors necessary for a more accurate representation. Once the analysis is completed, the identified factors can be appropriately labeled.

Table 7.

Description of Correlation Coefficient Scale

Scale of Correlation	Description of Correlation
±0.90 - ± 1.00	Very high
±0.70 – ±0.89	High
±0.5 - ±0.69	Moderate
±0.30 - ±0.49	Low
±0.00 - ±0.29	Negligible

Normal Distribution Test

To evaluate research data and its variable's normality by applying skewness and kurtosis coefficients. These statistical measures help determine whether the data distribution is symmetrical (skewness) and the degree to which the distribution is peaked or flat (kurtosis). Analyzing these coefficients provides insight into whether the data deviates from a normal distribution, which is essential for ensuring the validity of further statistical tests. The skewness and kurtosis values for all dimensions, as presented in table 8, fall within the acceptable range for a normal distribution. In particular, the skewness acceptable values should be in the range of minimum value of (-2) to maximum value of (2), and the kurtosis coefficients acceptable values should be in the range of minimum value from -7 to maximum value 7, indicating that the data aligns with the assumptions of normality. These results suggest that the study data adhere to a normal distribution, indicating that the data is appropriate for conducting the subsequent statistical analyses.

Table 8.

Skewness and Kurtosis values for the study variables

Dimensions	Sub-dimensions	Skewness	Kurtosis
Rational Decision-making	Intelligence gathering	-0.676	1.718
	Analysis and Design	-0.734	2.412
	Choice phase	-0.884	1.248
Machine Learning	Supervised Learning	0.196	-0.318
	Unsupervised Learning	-0.263	-0.439
Trust		-0.018	0.496

Multiple Regressions

Given that normality, validity, and reliability were established, regression analysis is applicable in this context, particularly after confirming the following underlying assumptions: The Durbin-Watson test was conducted to ensure the independence of errors, with a value close to 2 indicating that this assumption is not violated.

Additionally, the Variance Inflation Factor (VIF) and tolerance values were analyzed to assess multi-collinearity. Specifically, if the VIF is less than 10 and the tolerance is greater than 0.2, the model does not violate the multi-collinearity assumption. As shown in table 9, the VIF values do not exceed 10, and the tolerance values go beyond 0.1. This shows that multi-collinearity is not a concern among the research variables.

Table 9.

Tolerance and VIF Tests for main hypothesis

Dimension	Tolerance	VIF
Supervised Learning	0.362	2.761
Unsupervised Learning	0.253	3.948
Trust	0.159	6.274

Table 10 presents the Durbin-Watson values, which range from 1.391 to 2.290. Since these values are approximately equal to two, it indicates that the residuals are not correlated with one another. As a result, the assumption of independence of errors is upheld.

Table 10.

Durbin-Watson tests for study hypotheses (H1:H4)

	Durbin-Watson
H1	1.660
H1a	2.078
H1b	2.015
H1c	1.391
H2	1.708
H2a	2.229
H2b	1.926
H2c	1.491
H3	1.830
H3a	1.803
H3b	1.903
H4	1.922
H4a	2.290
H4b	2.027
H4c	1.726

Reliability and Validity

Cronbach's Alpha (α) used to measure the internal consistency of the data showing the reliability analysis. The acceptable level suggested by (Sekaran and Bougie, 2016) (Alpha (**α**) ≥ 0.7), the coefficients are in table 6. To assess the validity of the questionnaire, the researcher employed various methods, including face validity and construct validity. Face validity evaluates the clarity of the items, the quality of their linguistic formulation, and their relevance to the dimension they represent, ensuring they are precise and clear for the respondents. This process included submitting the initial version of the questionnaire to a panel of expert reviewers consisting of proficient ML and academic professionals in the field of management. Their feedback recommendations were incorporated, and the necessary modifications were made, with the finalized questionnaire presented in Appendix A.

To assess the validity of the construct for each item measuring the variable and its alignment with the intended construct, CFA was performed. This analysis verified the validity of the measures in the research and assessed their convergent validity by examining the factor loadings for each item.

The variables were further evaluated using the comparative Fit Index (CFI), Discriminant Validity, and Composite Reliability. Several key indicators were assessed to determine the goodness of fit for the study's measures as well as the overall model (Sarstedt et al., 2017). Table 11 presents the most common indicators that used in further analysis.

Table 11.

Goodness of fit Indicators for study model

Indicator	**The value indicating good conformity**
(5-1)	(CMIN/DF)
CFI=>0.90	(Comparative Fit Index)
TLI>=0.90	(Tucker Lewis Index)
IFI>=0.90	(Incremental Fit Index)
0 < RMSEA < 0.08	(Root Mean Square Error of Approximation)

Machine Learning (Independent Variable)

Table 12 demonstrates a high level of machine learning adoption in Jordan. The overall calculated mean of the research sample's ratings for the ML dimension was 3.73, indicating a strong evaluation score. Furthermore, the table reveals that the arithmetic means for the sub-dimensions ranged from 3.63 to 3.84, with the Supervised Learning dimension having a mean of 3.84 and Unsupervised Learning a mean of 3.63.

Table 12.

Mean, STD, importance, and ranking of (ML: SML, UNSML) independent variables

Sub-dimensions	**Mean**	**STD**	**Degree**
Supervised Learning	3.84	0.51	Agree
Unsupervised Learning	3.63	0.66	Agree
Machine Learning	3.73	0.53	Agree

To gain a detailed understanding of the level of machine learning in Jordan, the arithmetic means, and STD of the study participants' ratings for each item within the sub-dimensions of the machine learning dimension was calculated separately. The results are presented in the following pages.

Supervised Machine Learning

Table 13 reveals that the means for the items range from 3.26 to 4.16. The highest mean, 4.16, corresponds to Item 1, "The use of supervised machine learning improves the accuracy of data analysis," while the lowest mean, 3.26, pertains to Item 9, "Using supervised machine learning improves the ability to incorporate preferences and priorities in the decision-making process." The overall mean for the Supervised Learning dimension is 3.84.

Table 13.

Mean and STD for supervised machine learning (SML) items

No	Item	Mean	STD	Degree
1	The use of SML improves the accuracy of data analysis.	4.16	0.60	Agree
2	SML enhances the identification and understanding of relevant variables and patterns.	4.10	0.62	Agree
3	Using SML enables more efficient and effective data gathering.	4.15	0.72	Agree
4	SML facilitates the discovery of valuable insights.	4.09	0.72	Agree
5	The use of SML improves the quality and reliability of information.	4.10	0.74	Agree
6	SML aids in identifying the optimal decision alternatives available.	3.39	0.87	Neither
7	The use of SML improves the accuracy and speed of evaluating decision alternatives.	3.49	0.87	Agree
8	SML enhances the assessment of potential consequences and risks associated with decision alternatives.	3.32	0.99	Neither
9	Using SML improves the ability to incorporate preferences and priorities.	3.26	1.02	Neither
10	The use of SML facilitates the documentation and justification and outcomes	3.99	0.62	Agree
11	SML helps in formulating comprehensive decision alternatives.	3.99	0.64	Agree
12	The use of SML assists in identifying and evaluating potential risks and uncertainties.	4.10	0.56	Agree
13	SML enhances the generation and evaluation of decision criteria.	4.04	0.73	Agree
14	Using SML improves the ability to simulate and predict the outcomes of decision alternatives.	3.98	0.66	Agree
15	The use of SML facilitates the identification of trade-offs and dependencies among decision alternatives.	3.41	0.90	Agree
	Supervised Learning	3.84	0.51	Agree

Unsupervised Machine Learning

Table 14 presents the mean values for various items related to unsupervised machine learning, with scores ranging from 3.34 to 4.03. The highest mean, 4.03, is for Item (6), which states, "Unsupervised machine learning aids in identifying the optimal decision alternative among available options during rational decision-making," indicating strong agreement among respondents regarding its usefulness in decision-making. Conversely, Item (3) has the lowest mean of 3.34, associated with the statement, "Using unsupervised machine learning enables more efficient and effective data gathering," suggesting less conviction among respondents about this benefit. Overall, the average mean for unsupervised learning is 3.63, reflecting a generally positive perception of its advantages, though there is variability in opinions regarding specific applications.

Table 14.

Mean and STD for unsupervised machine-learning(UNSML) items

No	Item	Mean	STD	Degree
1	The use of UNSML improves the accuracy of data analysis	3.38	0.91	Neither
2	UNSML enhances the identification and understanding of relevant variables and patterns.	3.39	0.92	Neither
3	Using unsupervised machine learning enables more efficient and effective data gathering.	3.34	0.94	Neither
4	UNSML facilitates the discovery of valuable insights.	3.45	0.92	Agree
5	Using unsupervised machine learning improves the quality and reliability of information.	3.95	0.65	Agree
6	UNSML aids in identifying the optimal decision alternative among available options.	4.03	0.68	Agree
7	The use of UNSML improves the accuracy and speed of evaluating decision alternatives.	3.89	0.67	Agree
8	UNSML enhances the assessment of potential consequences and risks associated with decision alternatives.	3.97	0.72	Agree
9	Using UNSML improves the ability to incorporate preferences and priorities in the decision-making process.	4.01	0.60	Agree
10	Using UNSML facilitates the documentation and justification of decision-making processes and outcomes.	3.55	0.81	Agree
11	UNSML helps in formulating comprehensive decision alternatives.	3.49	0.88	Agree
12	The use of UNSML assists in identifying and evaluating potential risks and uncertainties.	3.42	0.83	Agree
13	UNSML enhances the generation and evaluation of decision criteria.	3.46	0.90	Agree
14	Using UNSML improves the ability to simulate and predict the outcomes of decision alternatives.	3.38	0.85	Neither
15	Using UNSML facilitates the identification of trade-offs and dependencies among decision alternatives during rational design-making.	3.71	0.87	Agree
	Unsupervised Learning	3.63	0.66	Agree

Rational Decision Making (Dependent Variable)

Table 15 shows that the level of RDM in Jordan is high. The calculated average of the research sample members’ ratings for the Rational Decision Making axis was

(3.71) with a high evaluation score. Table 15 also shows that the arithmetic averages for the sub-dimensions ranged between (3.47-3.86), the mean of dimension (Intelligence gathering phase) reached (3.86), the mean of (Analysis and Design phase) reached (3.76), the mean of (Choice phase) reached (3.47).

Table 15.

Mean, STD, importance, and ranking of dependent variable

No	Sub-dimensions	Mean	Std. Deviation	Degree
1	Intelligence Gathering phase	3.86	0.56	Agree
2	Analysis and Design phase	3.76	0.66	Agree
3	Choice phase	3.47	0.79	Agree
	Rational Decision Making	3.71	0.58	Agree

To know the level of Rational Decision Making in Jordan in detail, the calculated means and STD of the research sample members' estimates for the items of each sub-dimensions of the Rational Decision Making axis were extracted separately, and the results are presented below:

Intelligence Gathering Phase

Table 16 illustrates the mean scores for various items related to the intelligence-gathering phase, which range from 3.43 to 4.03. Among these items, Item 2 received the highest mean score, indicating a solid perception of its effectiveness or relevance within this phase. In contrast, Item 4 had the lowest mean score, explaining that respondents may view it as less impactful or relevant than the other items. The overall mean for the intelligence gathering phase is 3.86, reflecting a generally positive evaluation across all items.

Table 16.

Mean and STD for intelligence gathering phase items

No	Item	Mean	STD	Degree
1	I double-check my information sources to be sure I have the right facts before making decisions.	3.99	0.76	Agree
2	I make decisions logically and systematically.	4.03	0.65	Agree
3	My decision-making requires careful thought.	3.99	0.69	Agree
4	In my opinion, local government gathers a lot of data on any opportunity to decide better for the digital transformation.	3.43	1.06	Agree
	Intelligence gathering phase	3.86	0.56	Agree

Analysis and Design Phase

Table 17 presents the mean scores for various items associated with the Analysis and Design phase, with values ranging from 3.43 to 3.99. Item 2 achieved the highest mean score, indicating that respondents view it as particularly effective or valuable within this phase. Conversely, Item 3 received the lowest mean score, explaining it may be perceived as less significant or influential compared to the other items. The overall mean for the analysis and design phase is 3.76, reflecting a generally favorable assessment across all items.

Table 17

Mean and STD for analysis and design phase items

No	Item	Mean	STD	Degree
1	When making a decision, I consider various options in terms of a specified goal.	3.87	0.74	Agree
2	I usually have a rational basis for making decisions.	3.99	0.60	Agree
3	In my opinion, local government uses new technologies rather than old methods for decision-making regarding digital transformation.	3.43	1.11	Agree
	Analysis and Design	**3.76**	**0.66**	**Agree**

Choice phase

Table 18 displays the mean scores for various items related to the Choice phase, with scores ranging from 3.36 to 3.54. Item 1 received the highest mean score, explaining that respondents perceive it as particularly effective or relevant in this phase. In contrast, Item 2 recorded the lowest mean score, suggesting that it may be viewed as less impactful or significant compared to other items. The overall mean for the choice phase is 3.47, reflecting a generally positive assessment of the items within this phase.

Table 18.

Mean and STD for choice phase items

No	Item	Mean	STD	Degree
1	In my opinion, whenever local government face a difficult situation, it is optimistic about finding a good solution for the digital transformation.	3.54	0.90	Agree
2	In my opinion, my local government does not delay decision-making for the digital transformation when- ever it needed before it is too late.	3.36	0.93	Neither
3	In my opinion, local government considers all the available alternatives for decision-making regarding the digital transformation.	3.50	0.88	Agree
	Choice phase	3.47	0.79	Agree

Trust (Mediating Variable)

The mean range values for the items measured in the study span from 3.48 to 3.99, as shown in table 19. This indicates that respondents rated the items positively, with higher values reflecting more remarkable agreement or a stronger presence of the measured attribute. Among these items, Item (5) had the highest mean score, suggesting respondents most favorably viewed it. In contrast, Item (6) received the lowest mean score, indicating that it was considered less favorably or had weaker support among the participants. The overall mean score for the Trust variable reached 3.79, which signifies a positive perception of trust among the respondents, averaging between a moderate and high level of agreement across all items measured. This overall mean indicates a relatively strong foundation of trust within the context of the study.

Table 19.

Mean and STD for trust items

No	Item	Mean	STD	Degree
1	In general, ML technology is trusted nowadays.	3.67	0.76	Agree
2	I trust the accuracy and reliability of ML technologies for digital transformation decisions.	3.89	0.62	Agree
3	I trust ML technologies can effectively support rational decision-making processes in digital transformation.	3.82	0.59	Agree
4	I feel confident in using ML technologies for decision-making tasks in digital transformation.	3.91	0.60	Agree
5	I believe ML technologies can provide valuable insights and recommendations for decision-making in digital transformation.	3.99	0.65	Agree
6	I positively perceive the benefits that machine learning technologies bring to decision-making processes in digital transformation.	3.48	0.71	Agree
	Trust	**3.79**	**0.51**	**Agree**

Correlation Coefficients Analysis

A correlation matrix was conducted to evaluate the correlation between the study variables, as presented in table 20. The correlation coefficients for the different sub-dimensions of the RDM variable range from 0.549 to 0.769, indicating moderately strong to solid relationships. Each of these correlations was statistically significant at the 0.01 level. The highest correlation was observed between the intelligence and choice phases, suggesting a strong connection between these two stages. In contrast, the lowest correlation was between the design and analysis phase and the choice phase, indicating a comparatively weaker but still significant relationship. In essence, the data reveals that the strength of the relationships between different phases varies, with some stages being more closely related to decision-making than others, as seen in the strongest and weakest correlations.

The correlation coefficient between the two sub-dimensions of the ML, SML, and UNSML is 0.643, as presented in table 20, indicating a moderately strong relationship, which is statistically significant at the 0.01 level. This means the likelihood of this result occurring by chance is very low.

Additionally, the correlations between the sub-dimensions of the ML variable and the RDM variable range between 0.611 and 0.811, all of which are also statistically significant at the 0.01 level. The most robust relationship was observed between unsupervised learning and the intelligence-gathering phase, showing that unsupervised learning strongly influences information gathering.

On the other hand, the weakest correlation occurred between the analysis and design phase and supervised learning, indicating a comparatively weaker connection between these aspects, though still statistically significant. This analysis highlights how different learning methods (supervised and unsupervised) relate differently to various phases of the dependent variable, with unsupervised learning having a particularly strong influence on intelligence gathering.

The table 20 also demonstrates that the correlation coefficients among the independent, dependent, and mediating variables' sub-dimensions range from 0.789 to 0.876. These coefficients represent solid relationships and are all statistically significant at the 0.01 level, meaning the probability of these results occurring by chance is extremely low. The strongest correlation was found between the intelligence-gathering phase and trust, indicating a close connection between the information-gathering process and the level of trust in decision-making.

Conversely, the weakest correlation between the design and analysis phase and trust was observed, suggesting a comparatively lower, though still significant, relationship between these aspects.

This comprehensive analysis sheds light on the intricate interrelationships among the study's variables, showing both areas of strong correlation (e.g., intelligence gathering and trust) and weaker connections (e.g., design and analysis with trust). These findings provide valuable insights into which phases are most influenced by trust in the study context.

Table 20.

Correlation Coefficients matrix between study variables

Sub-dimensions	Intelligence gathering phase	analysis & Design phase	Choice phase	SML	UNSML	Trust
Intelligence gathering phase	1					
Analysis & Design phase	0.659**	1				
Choice phase	0.769**	0.549**	1			
SML	0.749**	0.611**	0.668**	1		
UNSML	0.811**	0.807**	0.688**	0.643**	1	
Trust	0.876**	0.789**	0.84**	0.795**	0.862**	1

(**) the correlation is significant (2-tailed) at the 0.01 level

Exploratory Factor Analysis

The researcher plans to condense the number of observed variables into smaller factors, aiming to uncover the relationships between them by employing Exploratory Factor Analysis (EFA), as Hinkin (1998) suggested. This study used the principal components analysis (PCA) technique as a starting point to extract the main factors. This was followed by the Promax rotation method with Kaiser normalization, which helped to refine and identify the underlying factors more clearly. PCA reduces complexity by grouping related variables, while Promax rotation allows for correlated factors, providing a more flexible and accurate representation of the data structure.

Exploratory Factor Analysis of ML Variables

Exploratory Factor Analysis (EFA) was performed to evaluate the structure of the questionnaire. Table 21 explains the rotation matrix for the items related to ML, which include two sub-dimensions, SML and UNSML, measured by a total of thirty items. The factor loadings for these items ranged from 0.410 to 0.843, all above the accepted threshold of 0.4, indicating that each item significantly contributes to its corresponding factor. The orthogonal rotation method successfully separated the items into two distinct factors, aligning with the theoretical structure of the questionnaire.

Moreover, the determinant of the matrix is 0.013, which is greater than (0), signifying there is no multi-collinearity and no autocorrelation issues within the variables. The Kaiser-Meyer-Olkin (KMO) test produced a value of 0.84, surpassing the minimum acceptable value of 0.50, which suggests that the sample size is adequate and supports reliable factor analysis results. Finally, Bartlett's Test yielded a value of 5145.632, with a significance level of 0.000 (below the 0.05 threshold), confirming the presence of statistically significant relationships among the sub-elements of the variables. This analysis provides strong evidence that the questionnaire is well-structured and that its items effectively measure the underlying sub-dimensions of ML.

Table 21.

Rotation matrix for the items of ML variables

	Component	
	1	2
Sup_Lea1	0.587	
Sup_Lea2	0.609	
Sup_Lea3	0.542	
Sup_Lea4	0.689	
Sup_Lea5	0.709	
Sup_Lea6	0.548	
Sup_Lea7	0.555	
Sup_Lea8	0.600	
Sup_Lea9	0.589	
Sup_Lea10	0.645	
Sup_Lea11	0.507	
Sup_Lea12	0.605	
Sup_Lea13	0.515	
Sup_Lea14	0.410	
Sup_Lea15	0.496	
Uns_Lea1		0.683
Uns_Lea2		0.818
Uns_Lea3		0.781
Uns_Lea4		0.843
Uns_Lea5		0.700
Uns_Lea6		0.680
Uns_Lea7		0.759
Uns_Lea8		0.621
Uns_Lea9		0.534
Uns_Lea10		0.609
Uns_Lea11		0.630
Uns_Lea12		0.564
Uns_Lea13		0.676
Uns_Lea14		0.655
Uns_Lea15		0.625
Determinant= 0.013 KMO=0.84 Bartlett's Test= 5145.632 (Sig.)= 0.000		

Exploratory Factor Analysis of RDM Variables

Table 22 displays the rotation matrix for the items assessing RDM, which consists of (3) sub-dimensions measured by ten items. The factor loadings for these items ranged from 0.54 to 0.82, all above the 0.4 threshold, indicating that each item strongly correlates with its respective factor. The orthogonal rotation method effectively grouped the items into three distinct aspects, matching the expected structure of the questionnaire.

Additionally, the determinant of the matrix is 0.011, which is greater than zero, confirming that there are no issues of autocorrelation or multi-collinearity among the variables. The Kaiser-Meyer-Olkin (KMO) test produced a value of 0.80, indicating that the sample size is adequate and that the data is suitable for factor analysis. Lastly, Bartlett's Test yielded a value of 1190.304, with a significance level of 0.000 (well below the 0.05 threshold), verifying statistically significant relationships among the sub-dimensions. This analysis demonstrates that the questionnaire effectively measures the sub-dimensions of Rational Decision Making, and the data is well-structured for further analysis.

Table 22.

Rotation matrix for the items of RDM variables

	Component		
	1	2	3
Intel1	0.82		
Intel2	0.81		
Intel3	0.60		
Intel4	0.54		
Design1		0.81	
Design2		0.69	
Design3		0.75	
Choice1			0.75
Choice2			0.70
Choice3			0.65
Determinant= 0.011 KMO=0.80			
Bartlett's Test= 1190.304 (Sig.)= 0.000			

Exploratory Factor Analysis of Trust

Table 23 presents the rotation matrix for the items related to the mediating variable, Trust, measured by six items. The factor loadings for these items ranged from 0.647 to 0.820, all exceeding the minimum threshold of 0.4, indicating that each item strongly correlates with the underlying factor. The orthogonal rotation successfully grouped all the items into a single factor, reflecting a cohesive trust measurement.

Moreover, the determinant of the matrix is 0.041, which is greater than zero, confirming that there is no autocorrelation or multi-collinearity issues among the variables. The Kaiser-Meyer-Olkin (KMO) test yielded a value of 0.824, suggesting that the sample size is sufficient and the data is suitable for factor analysis. Finally, Bartlett’s Test resulted in a value of 435.701, with a significance level of 0.000 (below the 0.05 threshold), indicating statistically significant relationships between the sub-elements of the variable. These results confirm that the items related to Trust are well-structured and effectively measure a single underlying factor, with the data demonstrating suitability for further analysis.

Table 23.

Rotation matrix for the items of Trust

	Component
	1
Trust1	0.792
Trust2	0.780
Trust3	0.820
Trust4	0.776
Trust5	0.768
Trust6	0.647
Determinant= 0.041 KMO=0.824	
Bartlett's Test= 435.701 (Sig.)= 0.000	

Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) is implemented to evaluate the proposed research model by confirming the relationships among the latent variable (theoretical concept) and its associated indicators (the specific items used to measure that concept). CFA helps ensure that the measurement model accurately reflects the theoretical structure of the variable, assessing whether the data fits the expected factor structure. By doing this, CFA provides strong evidence for both the validity (how well the items represent the construct) and the reliability (consistency of measurement) of the constructs within the model. In summary, CFA is a key step in verifying that the questionnaire and its items effectively capture the theoretical framework they are intended to measure.

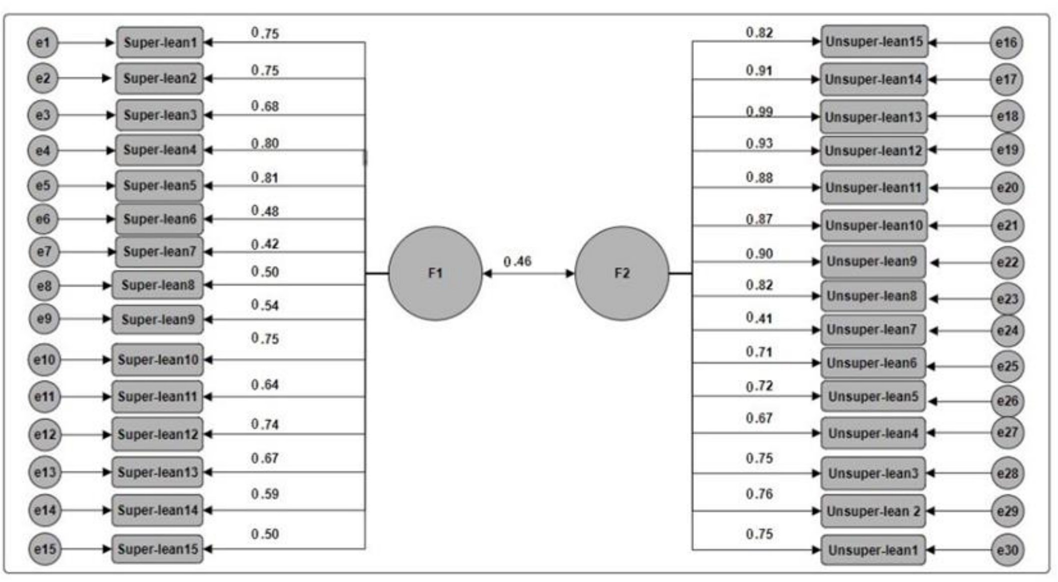
Confirmatory Factor Analysis ML Variables

The purpose of using Confirmatory Factor Analysis (CFA) is to validate the proposed study model, which includes the latent variable (an unobserved theoretical concept) and the specific indicators or items implemented to evaluate this variable. Construct validity is confirmed when the standardized regression weights for the relationships among the latent variable and its indicators exceed the threshold of 0.40, indicating strong connections between the constructs and their measures.

Figure 3 visualizes the CFA for the Machine Learning construct, illustrating how the latent variable (Machine Learning) relates to its corresponding indicators. This helps demonstrate that the model accurately represents the structure and relationships of the variable, confirming that the items are valid measures of the underlying concept.

Figure 3

Confirmatory factor analysis of ML



Confirmatory Factor Analysis RDM and Trust

In Confirmatory Factor Analysis (CFA), standardized regression weights quantify the strength and direction of the relationships among the latent variable (the construct) and its indicators (measurable items). When these weights surpass the 0.40 threshold, it indicates a strong and significant relationship, suggesting that the indicators are reliable measures of the latent variable. This threshold is commonly used in social sciences to ensure the measurement model is valid, meaning the indicators are relevant and accurately reflect the underlying construct.

Figure 4 illustrates the CFA for the RDM construct, showing how the latent variable connects with its associated indicators. Similarly, figure 5 presents the CFA for Trust, demonstrating the relationships among the latent variable and its corresponding indicators. In both figures, the regression weights offer insights into the strength of these connections, further confirming the appropriateness of the indicators in measuring their respective constructs.

Figure 4
CFA of RDM

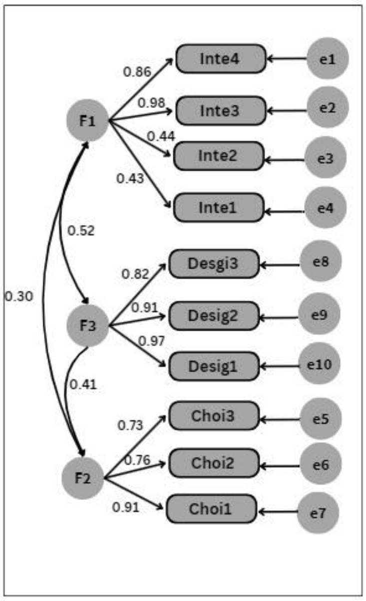
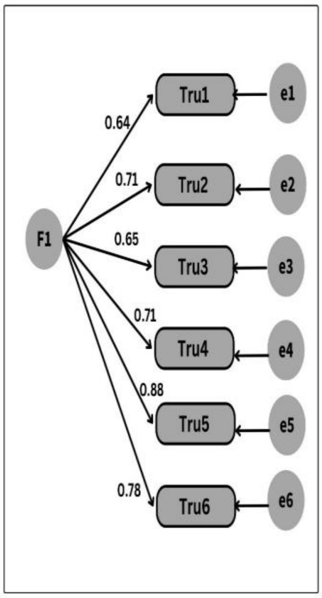


Figure 5
CFA of trust



Hypotheses Testing

In this research, the researcher used both SPSS and AMOS software to evaluate the proposed hypotheses, facilitating a robust analysis of the relationships between variables, including those involving mediators. SPSS (Statistical Package for the Social Sciences) was used for descriptive and inferential statistical analysis. In contrast, AMOS (Analysis of Moment Structures) provided structural equation modeling (SEM) capabilities, allowing for exploring complex interrelationships among the study variables. The integration of these tools enabled a comprehensive examination of the proposed hypotheses, which consist of five primary hypotheses and thirteen sub-hypotheses. This approach ensures a detailed understanding of both direct and mediated effects, enhancing the study's analytical depth and the validity of its findings. A regression analysis was performed to evaluate the hypothesis (H1-H4).

Relationship between SML and RDM

Evaluating the first hypothesis (H1) analysis examines whether SML has a positive influence on RDM within Jordan's e-government. As shown in table 24, the analysis reveals the following key findings; Beta value (0.770); represents the strength and direction of the correlation among SML and RDM.

A Beta value indicates a strong positive effect, meaning that as SML increases, RDM improves significantly. The T-value tests whether the Beta value is statistically significant where the T-value (14.208) is well above the typical threshold (generally around 2), confirming that this positive relationship is not due to chance and is statistically significant.

The correlation coefficient (R) is 0.770, indicating a strong positive linear correlation between SML and RDM. This means that as SML increases, RDM tends to increase as well. The coefficient of determination (R^2) is 0.592, suggesting that approximately 59.2% of the variability in RDM can be explained by SML. This is a significant proportion, indicating that the model has substantial explanatory power.

The Lower Limit Confidence Interval (LLCI) is 0.759, and the Upper Limit Confidence Interval (ULCI) is 1.005 at a 95% confidence level for the correlation coefficient. Since this interval does not include zero, it confirms the statistical significance of the effect of supervised machine learning on RDM.

The F-statistic is calculated at 201.874, which examines the overall significance of the regression model. A high F-value signifies that the model provides a significant improvement in predicting RDM compared to using just the mean of the dependent variable. The significance level (Sig.) associated with the F-statistic is 0.000, a p-value less than 0.001. This indicates that the overall regression model is highly significant, reinforcing the effectiveness of SML in predicting RDM.

In summary, these results demonstrate a strong, statistically significant positive impact of SML on RDM in Jordan's e-government digital transformation efforts. Therefore, hypothesis H1 is accepted.

Table 24.

Regression results for the relationship between SML and RDM

Independent **variable**	Unstandardized Coefficients		Standardized Coefficients		**LLCI**	**ULCI**	**R**	**R^2**	**F**	**Sig.**
	B	**Std. Error**	Beta	**T**						
Constant	0.328	0.240		1.363	-0.147	0.803	0.770	0.592	201.874	0.000
SML	0.882	0.062	0.770	14.208	0.759	1.005				

Evaluating the H1a sub-hypothesis to examine the effect of SML on the intelligence gathering phase of RDM within the context of digital transformation at Jordan's e-government. As shown in table 25, the results highlight the following key points: Beta value (0.749): This shows a strong positive relationship between SML and the intelligence-gathering phase.

A Beta value suggests that improvements in SML significantly enhance the intelligence-gathering process, which is critical for RDM.

T-value (13.314); tests the statistical significance of the Beta value. With a T-value well above the standard significance threshold, the relationship is confirmed to be statistically significant and not due to random chance.

The value of R (Correlation Coefficient): 0.749, a strong positive linear correlation among SML and the intelligence gathering phase of RDM. The R-value indicates a strong positive correlation. Also, the R^2 value (0.560) explains how much of the variation in the intelligence-gathering phase of RDM is accounted for by SML. This means that 56% of the variability in intelligence gathering can be explained by SML, indicating a substantial impact.

The LLCI: 0.706 and ULCI: 0.952 at the 95% confidence interval for the coefficient. Since the interval does not include zero, it confirms the statistical significance of supervised machine learning's effect.

F-statistic: 177.263 a high F-value reflects that the model significantly improves prediction over using the mean of the dependent variable alone. A p-value of 0.000 ($p < 0.001$) signifies that the overall regression model is highly significant.

In summary, these results present a significant positive effect of SML on the intelligence gathering phase of RDM within Jordan’s e-government digital transformation. Thus, the sub-hypothesis H1a is accepted.

Table 25.

Regression results for the relationship between SML and the intelligence gathering phase of RDM

Independent variable	Unstandardized Coefficients		Standardized Coefficients		**LLCI**	**ULCI**	**R**	**R^2**	**F**	**Sig.**
	B	**Std. Error**	Beta	**T**						
Constant	0.679	0.241		2.817	0.202	1.155	0.749	0.560	177.263	0.000
SML	0.829	0.062	0.749	13.314	0.706	0.952				

To test the H1b sub-hypothesis to assess the effect of SML on the analysis and design phase of RDM within the context of digital transformation in Jordan's e-government.

The results, as shown in table 26, reveal the following: Beta value (0.611): This reflects a moderately strong positive correlation between SML and the analysis and design phase. A Beta value suggests that improvements in SML have a significant positive effect on this phase of RDM.

T-value (9.098): This test measures the statistical significance of the Beta value. A T-value well above the typical threshold for significance confirms that this relationship is statistically significant and not due to chance.

The value of R (Correlation Coefficient): 0.611 measures a strong positive linear relationship between SML and the analysis and design phase of RDM. The R-value indicates a strong positive correlation. Also, R^2 value (0.373): explains how much of the variability in the analysis and design phase is accounted for by SML. This indicates that 37.3% of the variation in this phase can be explained by the model, demonstrating a meaningful impact.

The LLCI: 0.625 and ULCI: 0.973 at the 95% confidence interval for the coefficient. Since the interval does not include zero, it confirms the statistical significance of supervised machine learning's effect.

F-statistic: 82.771, a high F-value reflects that the model significantly improves prediction by using the mean of the dependent variable alone. A p-value of 0.000 ($p < 0.001$) signifies that the overall regression model is highly significant.

In summary, these findings show a significant positive effect of SML on the analysis and design phase of RDM within Jordan’s e-government initiatives in digitalization. Therefore, the sub-hypothesis H1b is accepted.

Table 26.

Regression results for the relationship between SML and the analysis & design phase of RDM

Independent variable	Unstandardized Coefficients		Standardized Coefficients		**LLCI**	**ULCI**	**R**	**R^2**	**F**	**Sig.**
	B	**Std. Error**	Beta	**T**						
Constant	0.695	0.340		2.044	0.023	1.367	0.611	0.373	82.771	0.000
SML	0.799	0.088	0.611	9.098	0.625	0.973				

To test the H1c sub-hypothesis to evaluate the effect of SML on the choice phase of RDM in the context of Jordan's e-government digitalization. The results, as shown in table 27, reveal the following:

Beta value (0.668): This explains a strong positive correlation between SML and the choice phase of RDM. A Beta value suggests that improvements in SML significantly enhance RDM during the choice phase.

T-value (10.569): indicates the statistical significance of the Beta value. With a T-value that is well above the typical threshold, the relationship is statistically significant and not due to random variation.

The value of R (Correlation Coefficient): 0.668 measures a strong positive linear correlation among SML in the choice phase of RDM. The R-value indicates a strong positive correlation. Also, the R^2 value (0.446) explains the variance ratio in the choice phase explained by SML. This means that the model accounts for 44.6% of the variability in this phase, indicating a considerable impact.

The LLCI: 0.842 and ULCI: 1.230 at the 95% confidence interval for the coefficient. Since the interval does not include zero, it confirms the statistical significance of supervised machine learning's effect.

F-statistic: 111.703 a high F-value reflects that the model significantly improves prediction over using the mean of the dependent variable alone. A p-value of 0.000 ($p < 0.001$) signifies that the overall regression model is highly significant.

In summary, these results demonstrate a significant positive effect of SML on the choice phase of RDM within Jordan’s e-government digital transformation. As a conclusion, the sub-hypothesis H1c is accepted.

Table 27.

Regression results for the relationship between SML and the choice phase of RDM

Independent variable	Unstandardized Coefficients		Standardized Coefficients		**LLCI**	**ULCI**	**R**	**R^2**	**F**	**Sig.**
	B	**Std. Error**	Beta	**T**						
Constant	-0.508	0.379		-1.338	-1.258	0.242	0.668	0.446	111.703	0.000
SML	1.036	0.098	0.668	10.569	0.842	1.230				

The relationship between UNSML and RDM.

To test hypothesis (H2) to evaluate the impact of UNSML on RDM in the context of Jordan's e-government digitalization. The data, as presented in table 28, demonstrate the following key findings:

Beta value (0.869): This indicates a robust positive correlation between UNSML and RDM. A Beta value suggests that improvements in UNSML have a significant and highly impactful effect on RDM processes.

T-value (20.720): which measures the statistical significance of the Beta value, is notably high. This confirms that the relationship between UNSML and RDM is statistically significant and not due to random chance.

The value of R (Correlation Coefficient): 0. 869 measures a strong positive correlation between UNSML and RDM. The R-value indicates a strong positive correlation. Also, the R^2 value (0.755): value explains the variance ratio in RDM that UNSML explains. The results suggest that the model accounts for 75.5% of the variability in RDM, highlighting a substantial impact.

The LLCI: 0. 693 and ULCI: 0.840 at the 95% confidence interval for the coefficient. Since the interval does not include zero, it confirms the statistical significance of unsupervised machine learning's effect.

F-statistic: 429.337, a high F-value reflects that the model significantly improves prediction by using the mean of the dependent variable alone. A p-value of 0.000 ($p < 0.001$) signifies that the overall regression model is highly significant.

In summary, these findings explain UNSML’s significant positive effect on RDM in the context of digital transformation at Jordan’s e-government. Therefore, hypothesis H2 is accepted.

Table 28.

Regression results for the relationship between UNSML and RDM

Independent variable	Unstandardized Coefficients		Standardized Coefficients		**LLCI**	**ULCI**	**R**	**R^2**	**F**	**Sig.**
	B	**Std. Error**	Beta	**T**						
Constant	0.931	0.136		6.825	0.661	1.201	0.869	0.755	429.337	0.000
UNSML	0.767	0.037	0.867	20.720	0.693	0.840				

To test sub-hypothesis H2a to assess the effect of UNSML on the intelligence-gathering phase of RDM within the context of digital transformation at Jordan's e-government. The results, as presented in table 29, reveal the following:

Beta value (0.811): This indicates a strong positive correlation among UNSML and the intelligence-gathering phase of RDM. A Beta value suggests that improvements in UNSML significantly enhance the intelligence-gathering process.

T-value (16.348): The high T-value confirms the statistical significance of the Beta value. A T-value means the relationship is robust and not due to random chance.

The value of R (Correlation Coefficient): 0.811, measures a strong positive linear relationship between UNSML and the intelligence gathering phase of RDM.

The R value indicates a strong positive correlation. Also, R^2 value (0.658): explains how much of the variability in the intelligence-gathering phase is accounted for by UNSML. This indicates that 65.8% of the variation in this phase is explained by the model, reflecting a substantial impact.

The LLCI: 0.607 and ULCI: 0.774 at the 95% confidence interval for the coefficient. Since the interval does not include zero, it confirms the statistical significance of unsupervised machine learning's effect.

F-statistic: 267.254 a high F-value reflects that the model significantly improves prediction over using the mean of the dependent variable alone. A p-value of 0.000 ($p < 0.001$) signifies that the overall regression model is highly significant.

In conclusion, the results show a significant positive effect of UNSML on the intelligence-gathering phase of RDM in the context of Jordan’s e-government digitalization. Therefore, the sub-hypothesis H2a is accepted.

Table 29.

Regression results for the relationship between UNSML and intelligence gathering phase of RDM

Independent variable	Unstandardized Coefficients		Standardized Coefficients		**LLCI**	**ULCI**	**R**	**R^2**	**F**	**Sig.**
	B	**Std. Error**	Beta	**T**						
Constant	1.352	0.156		8.677	1.044	1.660	0.811	0.658	267.254	0.000
UNSML	0.691	0.042	0.811	16.348	0.607	0.774				

To test sub-hypothesis H2b to evaluate the impact of UNSML on the analysis and design phase of RDM within the context of digital transformation at Jordan's e-government. The results, as presented in table 30, indicate the following:

Beta value (0.807): This reflects a strong positive correlation between UNSML and the analysis and design phase of RDM. A Beta value suggests that improvements in UNSML have a significant positive effect on this phase.

T-value (16.106): This supports the statistical significance of the Beta value and confirms that the relationship is robust and not due to random variability.

The value of R (Correlation Coefficient): 0.807 measures a strong positive linear relationship between UNSML and the analysis and design phase of RDM. The R-value indicates a strong positive correlation. Also, the R^2 value (0.651) explains the proportion of variance in the analysis and design phase that is accounted for by

UNSML. Results show that the model explains 65.1% of the variability in this phase, highlighting a substantial impact.

The LLCI: 0.712 and ULCI: 0.912 at the 95% confidence interval for the coefficient. Since the interval does not include zero, it confirms the statistical significance of unsupervised machine learning's effect.

F-statistic: 259.394 a high F-value reflects that the model significantly improves prediction over using the mean of the dependent variable alone. A p-value of 0.000 ($p < 0.001$) signifies that the overall regression model is highly significant.

In summary, these findings show a significant positive effect of UNSML on the analysis and design phase of RDM in the context of Jordan's e-government digitalization. Therefore, the sub-hypothesis H2b is accepted.

Table 30.

Regression results for the relationship between UNSML and the analysis & design phase of RDM

Independent variable	Unstandardized Coefficients		Standardized Coefficients		**LLCI**	**ULCI**	**R**	**R^2**	**F**	**Sig.**
	B	**Std. Error**	Beta	**T**						
Constant	0.815	0.186		4.382	0.447	1.182	0.807	0.651	259.394	0.000
UNSML	0.812	0.050	0.807	16.106	0.712	0.912				

To evaluate sub-hypothesis H2c to determine the impact of UNSML on the choice phase of RDM within the e-government of Jordan digitalization. The results, as shown in table 31, reveal the following key findings:

Beta value (0.688): This shows a strong positive correlation between UNSML and the choice phase of RDM. A Beta value suggests that enhancements in UNSML significantly improve this phase.

T-value (11.181): This high T-value further supports the statistical significance of the Beta value. A T-value indicates that the observed relationship is robust and unlikely to have occurred by chance.

The value of R (Correlation Coefficient): 0.688 measures a strong positive linear relationship between UNSML and the choice phase of RDM. The R-value indicates a strong positive correlation. Also, R^2 value (0.474): signifies the proportion of variance in the choice phase that UNSML can explain. This shows that the model accounts for 47.4% of the variability in this phase, indicating a meaningful impact.

The LLCI: 0.677 and ULCI: 0.967 at the 95% confidence interval for the coefficient. Since the interval does not include zero, it confirms the statistical significance of unsupervised machine learning's effect.

F-statistic: 125.020 a high F-value reflects that the model significantly improves prediction over using the mean of the dependent variable alone. A p-value of 0.000 ($p < 0.001$) signifies that the overall regression model is highly significant.

In summary, the findings demonstrate a significant positive effect of UNSML on the choice phase of RDM in the context of digital transformation in Jordan's e-government. Therefore, the sub-hypothesis H2c is accepted.

Table 31.

Regression results for the relationship between UNSML and choice phase of RDM

Independent variable	Unstandardized Coefficients		Standardized Coefficients		**LLCI**	**ULCI**	**R**	**R^2**	**F**	**Sig.**
	B	**Std. Error**	Beta	**T**						
Constant	0.486	0.271		1.793	-0.050	1.022	0.688	0.474	125.020	0.000
UNSML	0.822	0.074	0.688	11.181	0.677	0.967				

The Relationship Between Machine Learning and Trust

To assess hypothesis H3 to examine the influence of ML on trust in the context of the e-government of Jordan digitalization. The findings, as presented in table 32, yield the following key results:

Beta value (0.917): This high Beta value indicates a strong positive correlation between ML and trust. A value of 0.917 suggests that as ML capabilities improve, trust in the digital transformation processes also significantly increases.

The substantial T-value of 27.018 further confirms the statistical significance of the relationship. This indicates that the observed positive impact is highly reliable and unlikely to be due to random variation.

The value of R (Correlation Coefficient): 0.917 measures a strong positive linear relationship between ML and trust. The R-value indicates a strong positive correlation. Also, the R^2 value (0.840) indicates that the model can explain 84% of the variance ratio in trust, showcasing a significant level of influence. This high R^2 value suggests that ML is pivotal in fostering trust in digital transformation initiatives.

The LLCI: 0.823 and ULCI: 0.953 at the 95% confidence interval for the coefficient. Since the interval does not include zero, it confirms the statistical significance of machine learning's effect.

F-statistic: 729.956 a high F-value reflects that the model significantly improves prediction over using the mean of the dependent variable alone. A p-value of 0.000 ($p < 0.001$) signifies that the overall regression model is highly significant.

In conclusion, the analysis demonstrates a significant positive effect of ML on trust within the framework of digital transformation in Jordan's e-government. Consequently, hypothesis H3 is accepted.

Table 32.

Regression results for the relationship between ML and trust

<table>
<tr><th rowspan="2">Independent variable</th><th colspan="2">Unstandardized Coefficients</th><th colspan="2">Standardized Coefficients</th><th rowspan="2">LLCI</th><th rowspan="2">ULCI</th><th rowspan="2">R</th><th rowspan="2">R^2</th><th rowspan="2">F</th><th rowspan="2">Sig.</th></tr>
<tr><th>B</th><th>Std. Error</th><th>Beta</th><th>T</th></tr>
<tr><td>Constant</td><td>0.478</td><td>0.124</td><td></td><td></td><td>0.233</td><td>0.723</td><td rowspan="2">0.917</td><td rowspan="2">0.840</td><td rowspan="2">729.956</td><td rowspan="2">0.000</td></tr>
<tr><td>ML</td><td>0.888</td><td>0.033</td><td>0.917</td><td>27.018</td><td>0.823</td><td>0.953</td></tr>
</table>

To evaluate the sub-hypothesis H3a to determine the effect of supervised machine learning on trust within the digitalization at the e-government of Jordan. The analysis, as shown in table 33, reveals the following key findings:

Beta value (0.795): This positive Beta value indicates a strong relationship between supervised machine learning and trust, suggesting that improvements in supervised machine learning directly contribute to increased trust among users.

The T-value of 15.425 indicates a statistically significant impact, reinforcing the reliability of the observed positive relationship. This high T-value suggests that the results are not due to random chance and confirms the strength of the effect.

The value of R (Correlation Coefficient): 0.795 measures a strong positive linear relationship between SML and trust. The R value indicates a strong positive correlation. Also, the R^2 value of 0.631 signifies that 63.1% of the variance ratio in trust can be explicated by the model. This indicates the substantial level of influence that supervised machine learning has on fostering trust in the context of digital transformation.

The LLCI is 0.70, and the ULCI is 0.91 at the 95% confidence interval for the coefficient. Since the interval does not include zero, it confirms the statistical significance of machine learning's effect.

F-statistic: 237.943, a high F-value reflects that the model significantly improves prediction by using the mean of the dependent variable alone. A p-value of 0.000 ($p < 0.001$) signifies that the overall regression model is highly significant.

In summary, the analysis shows a significant positive influence of SML on trust within the Jordanian digital transformation efforts. Therefore, sub-hypothesis H3a is accepted.

Table 33.

Regression results for the relationship between SML and trust

Independent variable	Unstandardized Coefficients		Standardized Coefficients		LLCI	ULCI	R	R^2	F	Sig.
	B	Std. Error	Beta	T						
Constant	0.709	0.202		3.512	0.31	1.11	0.795	0.631	237.943	0.000
SML	0.804	0.052	0.795	15.425	0.70	0.91				

To assess the sub-hypothesis H3b and evaluate the influence of UNSML on trust within the context of DT at the e-government. The findings, as outlined in table 34, are as follows:

Beta value (0.862): This positive Beta value indicates a robust relationship between UNSML and trust. It suggests that enhancements in unsupervised machine learning are associated with increased levels of trust among users.

The T-value of 20.004 reflects a statistically significant impact, confirming that the relationship is strong and not a result of random variation. Such a high T-value emphasizes the reliability of the observed positive effect.

The value of R (Correlation Coefficient): 0.862, measures a strong positive linear correlation between UNSML and trust. The R-value indicates a strong positive correlation. Also, The R^2 value of 0.742 explains that UNSML can account for 74.2% of the variance ratio in trust. This suggests a significant influence of UNSML on building trust in the digital transformation process.

The LLCI: 0.605 and ULCI: 0.737 at the 95% confidence interval for the coefficient. Since the interval does not include zero, it confirms the statistical significance of supervised machine learning's effect.

F-statistic: 400.141, a high F-value reflects that the model significantly improves prediction by using the mean of the dependent variable alone. A p-value of 0.000 ($p < 0.001$) signifies that the overall regression model is highly significant.

In conclusion, the results demonstrate a substantial influence of UNSML on trust within digitalization initiatives. Therefore, sub-hypothesis H3b is accepted.

Table 34.

Regression results for the relationship between UNSML and trust

Independent variable	Unstandardized Coefficients		Standardized Coefficients		**LLCI**	**ULCI**	**R**	**R^2**	**F**	**Sig.**
	B	**Std. Error**	Beta	**T**						
Constant	1.360	0.124		10.996	1.115	1.605	0.862	0.742	400.141	0.000
UNSML	0.671	0.034	0.862	20.004	0.605	0.737				

The Relationship between Trust and RDM

Examining the H4 hypothesis to evaluate the effect of trust on RDM in the digitalization initiatives at the Jordanian e-government. The results, as presented in table 35, are as follows:

Beta value (0.949): This strong positive Beta value indicates a robust relationship between trust and RDM. The statement suggests that increased levels of trust can positively and significantly impact RDM outcomes.

T-value (35.643): The exceptionally high T-value signifies a statistically significant impact, confirming that the observed relationship is strong and reliable, rather than a result of random chance.

The R (Correlation Coefficient) value, 0.949, measures a strong positive linear relationship between trust and the RDM. The R-value indicates a strong positive correlation. Additionally, the R^2 value of 0.901 explains that about 90.1% of the variance in rational decision-making (RDM) is attributable to the levels of trust. This substantial figure reflects trust's critical role in enhancing RDM processes.

The LLCI 1.02 and ULCI: 1.13 at the 95% confidence interval for the coefficient. Since the interval does not include zero, it confirms the statistical significance of trust’s effect.

F-statistic: 1270.414 a high F-value reflects that the model significantly improves prediction over using the mean of the dependent variable alone. A p-value of 0.000 ($p < 0.001$) signifies that the overall regression model is highly significant.

In conclusion, the analysis confirms a significant positive impact of trust on RDM within the digitalization initiatives. Consequently, the H4 hypothesis is accepted.

Table 35.

Regression results for the relationship between trust and RDM

Independent variable	Unstandardized Coefficients		Standardized Coefficients		**LLCI**	**ULCI**	**R**	R^2	**F**	**Sig.**
	B	**Std. Error**	Beta	**T**						
Constant	-0.367	0.115		-3.179	-0.60	-0.14	0.949	0.901	1270.414	0.000
Trust	1.075	0.030	0.949	35.643	1.02	1.13				

To evaluate the H4a sub-hypothesis to assess the effect of trust on the intelligence gathering phase of RDM in the digitalization transformation. The results, as shown in table 36, are as follows:

Beta value (0.876): This positive Beta value explains a strong relationship between trust and the intelligence-gathering phase of RDM. It implies that higher levels of trust are associated with more effective and informed intelligence-gathering processes.

The high T-value of 21.393 demonstrates statistical significance, confirming that the observed effect is robust and unlikely to have occurred by chance.

The value of R (Correlation Coefficient): 0.876 measures a strong positive linear relationship between trust and the intelligence-gathering phase of RDM. The R-value indicates a strong positive correlation.

Therefore, the R^2 value of 0.767 suggests a strong relationship, indicating that trust levels account for approximately 76.7 % of the variability in the intelligence-gathering phase of RDM.

The LLCI: 0.869 and ULCI: 1.046 at the 95% confidence interval for the coefficient. Since the interval does not include zero, it confirms the statistical significance of trust's effect.

F-statistic: 457.650, a high F-value reflects that the model significantly improves prediction by using the mean of the dependent variable alone. A p-value of 0.000 ($p < 0.001$) signifies that the overall regression model is highly significant.

In conclusion, the analysis supports the notion that trust significantly positively impacts the intelligence-gathering phase of RDM in the digitalization efforts at the e-government. Therefore, the H4a sub-hypothesis is accepted.

Table 36.

Regression results for the relationship between trust and intelligence gathering phase of RDM

Independent variable	Unstandardized Coefficients		Standardized Coefficients		**LLCI**	**ULCI**	**R**	**R^2**	**F**	**Sig.**
	B	**Std. Error**	Beta	**T**						
Constant	0.224	0.171		1.308	-0.115	0.563	0.876	0.767	457.650	0.000
Trust	0.958	0.045	0.876	21.393	0.869	1.046				

To evaluate the H4b sub-hypothesis to determine the effect of trust on the analysis and design phase of RDM in the context of digitalization at the e-government. The results, as illustrated in table 37, reveal the following:

Beta value (0.789): This positive Beta value signifies a strong relationship between trust and the analysis and design phase of RDM. It suggests that higher levels of trust contribute to more effective analysis and design processes.

The T-value of 15.119 shows that the influence of trust is statistically significant, confirming the reliability of the findings and suggesting that the relationship observed is not a random chance.

The value of R (Correlation Coefficient): 0.789, measures a strong positive linear relationship between trust and the analysis and design phase of RDM. The R-value indicates a strong positive correlation. Also, The R^2 value of 0.622 explains that 62.2% of the variance ratio in the analysis and design phase can be explained by trust. This substantial percentage highlights trust's critical role in facilitating practical analysis and design activities during the digital transformation process.

The LLCI: 0.89 and ULCI: 1.15 at the 95% confidence interval for the coefficient. Since the interval does not include zero, it confirms the statistical significance of trust’s effect.

F-statistic: 228.596 a high F-value reflects that the model significantly improves prediction over using the mean of the dependent variable alone. A p-value of 0.000 ($p < 0.001$) signifies that the overall regression model is highly significant.

In summary, the analysis confirms that trust positively influences the analysis and design phase of RDM in Jordan's digital transformation efforts. Consequently, the H4b sub-hypothesis is accepted.

Table 37.

Regression results for the relationship between trust and analysis & design phase of RDM

Independent variable	Unstandardized Coefficients		Standardized Coefficients		LLCI	ULCI	R	R^2	F	Sig.
	B	Std. Error	Beta	T						
Constant	-0.106	0.258		-0.409	-0.62	0.40	0.789	0.622	228.596	0.000
Trust	1.019	0.067	0.789	15.119	0.89	1.15				

To assess the H4c sub-hypothesis to examine the influence of trust on the choice phase of RDM within the digitalization process at the e-government. The results, as shown in table 38, highlight the following key findings:

Beta Value (0.840): This positive Beta value suggests a strong relationship between trust and the choice phase of rational decision-making. It implies that increased levels of trust enhance the RDM during the choice phase.

The T-value of 18.220 explains that the correlation between trust and the choice phase is statistically significant. This reinforces the credibility of the findings, suggesting that the observed effects are unlikely to be the result of chance.

The value of R (Correlation Coefficient): 0.840 measures the strength and direction of the linear relationship between trust and the choice phase of RDM. The R-value indicates a strong positive correlation. Additionally, the R^2 value of 0.705 indicates that trust explains 70.5% of the variance in the choice phase.

The LLCI: 1.15 and ULCI: 1.43 at the 95% confidence interval for the coefficient. Since the interval does not include zero, it confirms the statistical significance of trust's effect.

F-statistic: 331.972, a high F-value reflects that the model significantly improves prediction by using the mean of the dependent variable alone. A p-value of 0.000 ($p < 0.001$) signifies that the overall regression model is highly significant.

In conclusion, the results support that trust positively influences the choice phase of RDM in the context of digitalization initiatives at e-government. Thus, the H4c sub-hypothesis is accepted.

Table 38.

Regression results for the relationship between trust and choice phase of RDM

Independent variable	Unstandardized Coefficients		Standardized Coefficients		**LLCI**	**ULCI**	**R**	**R^2**	**F**	**Sig.**
	B	**Std. Error**	Beta	**T**						
Constant	-1.417	0.271		-5.238	-1.95	-0.88	0.840	0.705	331.972	0.000
Trust	1.288	0.071	0.840	18.220	1.15	1.43				

Mediating role of Trust on ML, RDM relationship

Examining the H5 hypothesis, using structural equation modeling (SEM) with the AMOS V23 software in conjunction with SPSS. Path analysis, a technique for exploring direct and indirect relationships between variables, was applied to assess the trust role between the (ML) and (RDM) relationships.

The goal of this analysis was to explore how machine learning directly influences decision-making, as well as its indirect effects through the mediation of trust within the framework of digital transformation. Table 39 presents the values associated with the direct and indirect impacts of the mediating variable (trust) on the relationship between ML and RDM. The path analysis shows that (ML) has a moderate direct impact on (RDM). The coefficient of 0.245 suggests that as ML is utilized, decision-making becomes more rational, although this effect is not overwhelming. The critical ratio (C.R.) of 3.885 confirms the statistical significance of this relationship, indicating that the adoption of ML contributes positively to decision-making processes. However, this direct influence is only part of the picture, as ML interacts with other variables that enhance its impact. A key finding is a strong relationship between ML and trust. With a high coefficient of 0.917 and a C.R. of 27.115, it is evident that using ML builds significant trust in the system. This relationship suggests that as ML tools are implemented, users are more confident in providing accurate, reliable, and transparent outcomes. Trust, in turn, plays a significant role in the overall process, acting as a critical bridge between the technical capabilities of ML and the human decision-making process.

Finally, the path analysis highlights the importance of trust as a mediator in the correlation between the dependent and independent variables of the study. Trust directly influences RDM with a strong coefficient of 0.725, showing that decision-making becomes considerably more rational as trust in ML increases. The indirect effect of ML on RDM through trust (0.664) is notably larger than its direct impact, illustrating that the real strength of ML's influence on decision-making comes from the trust it fosters. This suggests that while ML alone can improve decision-making, its effects are amplified when trust is present, making trust a vital factor in achieving optimal outcomes in decision-making, particularly in environments undergoing digital transformation. This leads to the support of hypothesis H5.

Table 39.

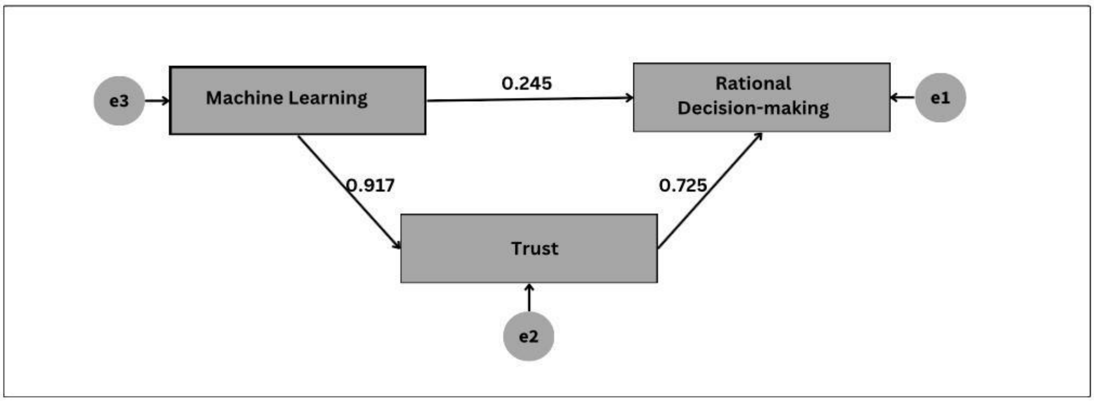
Path analysis for the effect of mediating variable (trust) on the correlation between ML and RDM

Impact direction	Direct effect	Sig.	Indirect effect	C.R.
ML → RDM	0.245	**	0.664	3.885
ML → Trust	0.917	**		27.115
Trust → RDM	0.725	**		11.497

Furthermore, figure 6 illustrates the role of trust in this correlation, highlighting its importance in enhancing RDM processes within digitalization initiatives.

Figure 6

Role of mediating variable (trust) on the correlation among ML and RDM



The path analysis for testing the H5a sub-hypothesis examines the relationship between (SML), trust, and (RDM) in digital transformation. The results reveal that SML has a small direct effect on RDM, with a coefficient of 0.047, which indicates that while SML contributes to decision-making, its direct impact is minimal. Despite the modest direct effect, the significance of this coefficient (with a p-value below 0.05) confirms that SML still contributes to decision-making, although not a dominant one. A much stronger relationship is found between SML and trust, with a coefficient of 0.795 and a C.R. of 15.481, indicating that SML greatly enhances trust in the system. This significant result suggests that applying supervised machine learning builds a substantial level of trust, which is essential for decision-makers to rely on ML processes. Trust, in turn, has a powerful direct impact on RDM, with a coefficient of 0.917 and a C.R. of 21.038, highlighting that trust is the most influential factor in improving rational decision-making. These results emphasize trust's critical role in connecting SML to more effective decision-making.

The analysis further confirms the indirect effect of SML on RDM through trust, with an indirect effect value of 0.728, which is significantly larger than the direct effect (0.047). This indicates that trust fully mediates the relationship between SML and RDM, as evidenced by the solid indirect effect and the statistical significance of all coefficients. In essence, trust amplifies the impact of SML on RDM, demonstrating that without faith, SML's influence on decision-making is minimal. These findings lead to the acceptance of hypothesis H5a. Figure 7 visually reinforces the role of trust, highlighting its centrality in enhancing RDM within these frameworks.

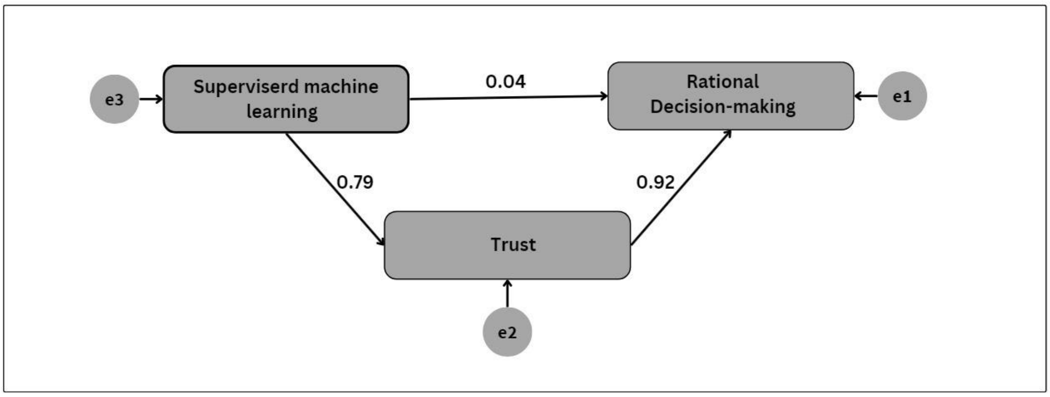
Table 40.

Path analysis for the effect of mediating variable(trust) on the correlation between SML and RDM

Impact direction	Direct effect	Sig.	Indirect effect	C.R.
SML → RDM	0.047	**	0.728	0.949
SML → Trust	0.795	**		15.481
Trust → RDM	0.917	**		21.038

Figure 7

Role of mediating variable (trust) on the correlation among SML and RDM



The path analysis for testing the H5b sub-hypothesis explores the relationship between (UNSML), trust, and (RDM) within the Jordanian e-government. The results show that UNSML has a moderate direct impact on RDM, with a coefficient of 0.199, suggesting that using UNSML positively influences decision-making. This direct effect is statistically significant, with a p-value below 0.05, indicating that while UNSML has a notable impact on RDM, it is not overwhelmingly strong. Nevertheless, the significance of this relationship confirms that UNSML acts as a crucial factor in RDM process and phases.

The analysis also reveals a strong relationship between UNSML and trust, with a coefficient of 0.862 and a critical ratio (C.R.) of 20.075, highlighting that UNSML significantly increases trust in the system. This finding suggests that as unsupervised machine learning is implemented, users develop a high level of trust in the outcomes it generates, which is crucial for its success. Trust, in turn, has a direct and substantial effect on RDM, with a coefficient of 0.778 and an equally high C.R. of 20.075. This indicates that trust is a powerful factor in enhancing rational decision-making, further reinforcing its importance in the overall process.

The path analysis supports the conclusion that trust is a partial mediator among UNSML and RDM. The indirect effect of UNSML on RDM through trust is 0.670, which, combined with the direct impact, shows that trust contributes to amplifying the influence of UNSML on decision-making. Although UNSML has a significant direct impact, its overall effect on decision-making is strengthened through trust, making it a critical mediator. These findings lead to the acceptance of hypothesis H5b, underscoring the partial mediation of trust in this relationship. Figure 8 visually illustrates this mediating role, emphasizing trust's critical importance in optimizing RDM.

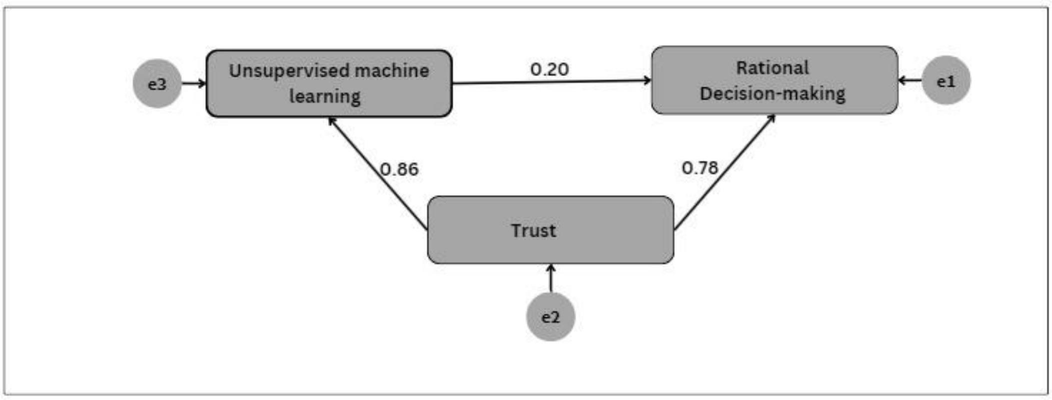
Table 41.

Path analysis for the effect of mediating variable (trust) on the correlation between UNSML and RDM

Impact direction	Direct effect	Sig.	Indirect effect	C.R.
UNSML → RDM	0.199	**	0.670	15.721
UNSML → Trust	0.862	**		20.075
Trust → RDM	0.778	**		20.075

Figure 8

Role of trust on the correlation between UNSML and RDM



Summary

The findings in this chapter present a comprehensive analysis of the relationships between ML, trust, and RDM among middle-level managers in Jordan's Ministry of Digital Economy. Descriptive statistics and inferential analyses are employed to test hypotheses, with the results revealing that trust plays a critical mediating role in enhancing the effectiveness of ML in decision-making. The chapter systematically discusses how ML improves RDM through various phases, such as intelligence gathering, analysis, and choice, while emphasizing the importance of trust in this process

CHAPTER V
Discussion

This chapter of this study addresses the findings and their implications for understanding the role of (ML) in enhancing (RDM) and trust within the context of digitalization, particularly in Jordanian e-government. Although ML has seen significant advancements, research exploring its impact on RDM and trust in the specific domain of e-government remains limited. In particular, the application of ML within Jordan's e-government framework and its influence on decision-making processes, alongside the mediating role of trust, has not been thoroughly investigated.

This research aims to fill that gap by empirically evaluating how ML functions contribute to RDM during digital transformation initiatives in Jordanian e-government. The research further explores the significant impact of trust as a mediator in the relationship, offering insights into how trust can enhance the effectiveness of ML in fostering more rational decisions. By addressing these gaps, this research provides additional insights to the existing literature on ML, trust, and decision-making in e-government, providing valuable knowledge for policymakers and practitioners working in digital transformation initiatives. The findings of this research not only provide a deeper understanding of these relationships but open doors for future studies in the intersection of ML, RDM, and trust within e-government contexts.

Gender Male\ female contribution

This transformation reflects a broader societal shift towards inclusivity and recognition of women's invaluable contributions to the field. As more women pursue education and careers in technology, the industry is witnessing a positive evolution towards greater gender equality, dismantling stereotypes and paving the way for a more balanced and dynamic workforce.

Age

The surge of young professionals gravitating towards middle-level management positions in the technology sector can be ascribed to various factors. Firstly, the digital age has created an environment where technology is seamlessly integrated into different business operations, making tech-savvy individuals well-suited for managerial roles. Growing up in the era of rapid technological advancement, young professionals possess an innate understanding of digital tools and platforms, providing them with a competitive edge in managing tech-centric teams. Additionally, the dynamic nature of the tech industry appeals to the innovative spirit and adaptability commonly associated with the younger workforce. As these individuals advance in their careers, they bring fresh perspectives, a collaborative mindset, and a natural affinity for emerging technologies, fostering a conducive environment for growth and development within middle-level management in the ever-evolving realm of technology.

Experience

Young professionals in technology positions often accumulate a considerable amount of experience at the beginning of their professional careers due to the high demand for their skills and the trend of early enrolment in tech jobs. The relentless pace of technological advancements has led to an increased demand for skilled individuals who can navigate and harness the power of cutting-edge tools and methodologies. In response to this demand, many young people opt for early entry into the workforce, seizing opportunities to contribute to innovative projects and gain hands-on experience. The dynamic nature of the tech industry encourages a culture of continuous learning, where professionals are compelled to stay abreast of the latest developments. As a result, these early-career individuals contribute meaningfully to their roles and accrue a wealth of experience over a shorter timeframe, positioning them as seasoned experts despite their relatively young age. This accelerated career trajectory is a testament to the unique demands and opportunities that characterize the vibrant landscape of technology-related occupations.

Education Level

The study results, as outlined in table 5, reveal a precise distribution of educational levels among the respondents, divided into four categories: Associate, Bachelor's, Master's, and Doctorate degrees. The findings indicate that bachelor's degree holders comprise the majority of the participants, representing 66.0% of the sample. This high percentage reflects a shift in recent years, where a Bachelor's degree has become the minimum requirement for government enrollment. The next largest group, at 22.7%, comprises individuals with a Master's degree, followed by those with a Doctorate at 9.9%. Only a small proportion, 1.4%, of respondents hold an Associate degree, underscoring the growing emphasis on higher academic qualifications within the target population.

This distribution suggests that the target population is well-educated, with the majority having attained a Bachelor's degree. The relatively low percentage of respondents with an Associate degree could be attributed to the fact that many government roles now require more advanced qualifications, making this category less prevalent. Conversely, the significant proportion of individuals with postgraduate qualifications (Master's and Doctorate degrees) highlights the advanced educational backgrounds of many participants, which may have implications for their perspectives and engagement with the subject matter of the study.

Relationship between SML and RDM

According to the relationship between SML and RDM, we answered the first research question that examined the impact of SML on RDM, where the analysis presented in Chapter 4, as summarized in table 42. The values for both Beta and T were positive and statistically significant, explaining a strong relationship between the variables. The R^2 value was also statistically significant, further validating the model. Moreover, the confidence interval, ranging from 0.759 to 1.005, reinforces the significance of the results, as it does not include zero. Based on these findings, the first main hypothesis (H1), which posits that SML positively influences RDM in Jordan's digital government transformation, is accepted.

Integrating AI technologies, especially ML, in government processes is a global trend, and this study highlights its significance in Jordan. The analysis uncovered a 59.2% correlation between SML and RDM, representing a moderate yet meaningful relationship. This moderate correlation could be due to numerous factors, such as the complexity of government workflows, the wide range of data sources, and the stage of digital transformation in the Jordanian e-government landscape. These outcomes agree with earlier researches (Sharma et al., 2020; Al-Mushayt, 2019; Kureljusic & Metz, 2023) and emphasize the significance of utilizing advanced ML in managing digital records and documents. Policymakers and IT professionals can use these insights to design strategies that enhance government processes' efficiency, accuracy, and security.

Furthermore, this research evaluates the correlation between SML and the first phase of RDM, the intelligence-gathering phase in digital transformation. The findings unveil a moderate but statistically significant correlation of 56.0%, shedding light on the influence of SML on the Intelligence phase of RDM. This mild strength of association implies a discernible yet not overwhelmingly strong connection. Potential factors contributing to this moderate correlation might include the complexity of intelligence-related tasks, data variability, or the intricate nature of governmental processes. It underscores the significance of leveraging advanced ML techniques to enhance the intelligence-gathering capabilities within the e-government. Policymakers and IT professionals can draw from these insights to formulate strategies that improve the performance and effectiveness of intelligence-related processes in the digital era.

The study also explored the relationship between SML and different phases of RDM, shedding light on specific dynamics within the digital transformation process. First, the analysis of the intelligence-gathering phase revealed a moderate but statistically significant correlation of 56.0%, underscoring SML's influence on RDM's intelligence-gathering activities in e-government. This association suggests that SML can improve the efficiency and accuracy of information collection, although complexities in governmental processes may contribute to a moderate effect size. Policymakers should capitalize on these insights to boost intelligence-related tasks within digital frameworks.

In contrast, the relationship between SML and the Analysis and Design phase showed a lower correlation of 37.3%, although it was still statistically significant. This weaker connection might arise from the complexity of designing and analyzing governmental systems and data. Policymakers and IT professionals should explore how to optimize the use of SML in this phase to improve the efficiency of record management design processes.

The study uncovered 44.6% correlation between SML and RDM for the choice phase. Although this might be considered low, it is nonetheless statistically significant. The findings suggest a complex landscape where various socio-economic and political factors influence technology adoption. Understanding these nuances is crucial, as they may provide insights into the RDM processes within the government of Jordan. Future research could investigate these contextual elements to enhance the strategic implementation of SML in the choice phase of RDM. Comparing results to related studies (Merkert et al., 2015; Loukili et al., 2023; Alexopoulos et al., 2019), this research demonstrates that SML positively influences all phases of rational decision-making, including intelligence gathering, analysis and design, and the choice phase. This reinforces the increasing body of evidence regarding the potential advantages of SML in advancing digital transformation initiatives within government sectors.

Relationship between UNSML and RDM

By examining the second research question, which analyzes the impact of (UNSML) on (RDM), the results summarized in Table 42 reveal a significant positive influence of UNSML on RDM within the digital transformation of Jordan's e-government. The Beta and T values were positive and statistically significant, along with the R^2 value, indicating a robust linear correlation among the variables. The confidence interval, ranging from 0.693 to 0.840, further reinforces the significance of these findings, with no zero values within the interval. Consequently, the second main hypothesis (H2) is accepted, confirming the positive influence of UNSML on decision-making processes.

This research uncovers a compelling relationship between UNSML and RDM, revealing a strong correlation of 75.5%. This robust connection underscores the positive role of UNSML in shaping decision-making. By integrating UNSML for tasks like data exploration, pattern recognition, and knowledge extraction, decision-makers can gain deeper insights from complex datasets, leading to more informed and rational choices. The results suggest that organizations and decision-makers should strategically incorporate UNSML techniques, such as clustering, dimensionality reduction, and anomaly detection, to enhance risk assessment, resource allocation, and strategic planning.

The study reveals a moderate correlation of 65.8% between UNSML and the intelligence phase of RDM in the e-government of Jordan. Although this connection is not overwhelming, the statistical analysis highlights UNSML's significant role in enhancing intelligence-gathering capabilities. UNSML contributes to acquiring, processing, and interpreting information, facilitating more robust RDM processes. The specific nature of e-government in Jordan, including its data types and regulatory environment, adds complexity to this relationship, which decision-makers should carefully consider.

UNSML also significantly contributes to the analysis and design phase, with a moderate correlation of 65.1%. This connection emphasizes the essential of UNSML indecision-making during digital transformation. The findings underscore that decision-makers should strategically utilize UNSML techniques to optimize processes related to designing and analyzing data. By doing so, they can improve decision-making effectiveness in Jordan's e-government.

Despite a relatively low correlation of 47.4%, UNSML demonstrates a statistically significant impact on the choice phase of RDM. While the numerical relationship may appear modest, UNSML still plays a critical role in influencing decisions during this phase. The study suggests that contextual factors, such as organizational culture, decision-making structures, and technological readiness, could influence the extent of UNSML's impact. Policymakers should not overlook UNSML's value in guiding decisions within this phase of digital transformation.

Overall, this research aligns with previous research (Usama et al., 2019; Alloghani et al., 2020) and confirms that UNSML positively influences all phases of RDM in digital transformation, including intelligence gathering, analysis and design, and the choice phase. It underscores UNSML's capacity to boost the efficiency and accuracy of decision-making and promote data-driven methodologies in Jordan's e-government context. Decision-makers and stakeholders should consider these findings to maximize the benefits of UNSML in digital governance transformation.

Relationship between ML and Trust

In addressing the third research question regarding the influence of (ML) on trust, our study's analysis demonstrates that ML has a positive and statistically significant effect on trust. The overall correlation between ML and trust is substantial, with a Beta value and a T-value, both statistically significant. The R^2 value indicates that ML explains 84.0% of the variance in trust. The confidence interval, ranging from 0.823 to 0.953, confirms this result, as no zero values are present. Consequently, the main hypothesis (H3) is accepted, affirming that ML significantly enhances trust in the e-government of Jordan.

Our research uncovers an 84.0% relationship between ML and trust, indicating a highly positive and significant correlation. This strong connection suggests that integrating ML technologies is pivotal in building trust across various digital platforms. The ability of machine learning (ML) to proceed with a huge amount of data, define patterns, and deliver accurate predictions is essential in building trust in e-government services. These results support previous findings, such as those by Ferrario et al. (2020) and Janssen et al. (2022), affirming that ML enhances trust in different domains, including e-government.

The study also investigates the influence of supervised machine learning (SML) on trust. The results show a meaningful positive relationship, with a beta value and a T-value, which are both statistically significant.

The R^2 value is 0.631, indicating a 63.1% correlation between SML and trust. The confidence interval between 0.7 and 0.91 indicates significance, and sub-hypothesis H3a is accepted. This moderate relationship demonstrates that while SML positively influences trust, the connection is not overwhelming. In the context of Jordanian e-government, understanding cultural factors, governmental structures, and public expectations is crucial for leveraging SML to foster trust. Policymakers should consider employing SML strategically to enhance trust in digital services. This can involve applying SML in areas like fraud detection, service personalization, and data privacy, which are critical to building public confidence in digital government platforms.

The analysis also indicates a strong positive impact of unsupervised machine learning (UNSML) on trust, as evidenced by statistically significant Beta and T-values. An R^2 value of 0.742 demonstrates a 74.2% correlation between UNSML and trust. The confidence interval, ranging from 0.605 to 0.737, confirms statistical significance, leading to the acceptance of sub-hypothesis H3b.

UNSML’s influence on trust-building in Jordanian e-government is robust, highlighting its potential in handling large datasets for pattern recognition, anomaly detection, and knowledge discovery. This connection between UNSML and trust suggests that decision-makers should integrate UNSML into trust-building initiatives to enhance the transparency and reliability of digital services. Its application in improving cybersecurity, data integrity, and fraud prevention can foster greater public confidence in digital government services.

The study confirms that both supervised and unsupervised ML positively influence trust in Jordan’s digital transformation, with stronger impacts seen from UNSML. Policymakers and IT professionals should strategically leverage both ML types to foster trust, addressing contextual factors unique to Jordan, such as public perceptions, cultural considerations, and governmental structures. Future research should explore how different ML methodologies and public expectations shape trust in e-government services.

Relationship between Trust and RDM

When examining the fourth question on the impact of trust on RDM, the analysis reveals robust values, with an R^2 value of 0.901, indicating that trust accounts for 90.1% of the variance in RDM. The confidence interval, which ranges from 1.02 to 1.13 and contains no zero values, further supports this conclusion. This leads to the acceptance of the hypothesis (H4), confirming the profound impact of trust on RDM. The exceptionally strong relationship 90.1% underscores the vital importance of trust in shaping effective decision-making. The results highlight that trust directly affects the rationality and success of decision-making processes. By fostering trust within government and among decision-makers, entities can ensure more informed, logical, and successful decision outcomes. Trust, in this context, becomes a key enabler of rational choices, facilitating clearer communication and better judgment.

The study uncovers a substantial 76.7% relationship between trust and the Intelligence-gathering phase of RDM. This phase, which involves gathering, processing, and interpreting information, is significantly influenced by the high level of trust. In the Jordanian e-government context, trust catalyzes information sharing, knowledge exchange, and collaboration, which are crucial for developing well-informed decisions. Building a high-trust environment encourages open communication and ensures more accurate and comprehensive intelligence gathering, leading to improved decision-making outcomes.

In the analysis and design phase, where data is interpreted, and solutions are designed, the relationship between trust and RDM is moderate, standing at 62.2%. While not overwhelmingly high, this statistically significant influence emphasizes that trust Serves a pivotal component in shaping how data is analyzed and decisions are structured. For decision-makers and subject matter experts involved in Jordan's e-government digital transformation, cultivating trust within teams is essential for effective collaboration in the analysis and design processes, ultimately resulting in more precise and impactful results.

The correlation between trust and the phase of choice is also significant, with a 70.5% connection. This phase, where the optimal course of action is selected, is heavily influenced by the degree of trust among subject matter expertise and decision-makers. Trust fosters confidence in the RDM process, allowing individuals to make more decisive and informed choices. In the Digitalization context, trust ensures that decision-makers are more certain of their choices, leading to better overall decision outcomes.

The study confirms that trust enhances rational decision-making across all phases of RDM in Jordan's digital transformation. The strong positive impact of trust—especially in the intelligence, analysis, and choice phases—highlights its essential function in fostering collaboration, confidence, and informed decision-making, and these results are supported by literature (Schmidt et al., 2020; Ingrams et al., 2022; Schwalb et al., 2022). Also, should prioritize cultivating trust within organizational structures and teams, as doing so will significantly enhance the effectiveness of decisions and the overall achievements of digitalization.

The mediating role of Trust in the relationship between ML and RDM

In exploring the fifth question regarding the mediating role of trust in the correlation between (ML) and (RDM), the analysis uncovers several significant findings related to the influence of trust. By examining the direct effects, the value of the direct effect of ML on RDM was found to be 0.245, while the impact of ML on trust, the mediator, was significantly higher at 0.917.

Additionally, the direct impact of trust on RDM was 0.725. These results indicate that trust significantly mediates, partially influencing the relationship between (ML) and (RDM). This suggests that while trust does not fully mediate the relationship, it is instrumental in shaping the dynamics between ML and decision-making. As a result, the primary hypothesis (H5), which proposed that trust acts as a mediator, is accepted.

In testing sub-hypothesis H5a, the values show that the direct effect of ML on RDM was 0.047, a notably small value. Meanwhile, the impact of ML on trust was 0.795, and the effect of trust on RDM was a substantial 0.917. The statistical significance of these values indicates that trust fully mediates the correlation between SML and RDM in the e-government's digital transformation process.

This proposes that when SML is employed, its influence on decision-making processes is entirely channeled through trust, meaning supervised ML's direct impact on RDM is minimal unless trust is established. Therefore, sub-hypothesis H5a is accepted.

Also, sub-hypothesis H5b, tested through, reveals that the direct effect of unsupervised ML on RDM was 0.199, while the impact of ML on trust was 0.862, and trust's direct effect on RDM was 0.778. These statistically significant values suggest that trust acts as a partial mediator in this relationship rather than comprehensively. In this case, unsupervised ML directly influences RDM, but trust enhances and strengthens this relationship. Hence, sub-hypothesis H5b is also accepted.

The mediating role of trust becomes particularly critical in understanding how organizations and governments can leverage machine learning technologies to improve decision-making processes. Trust enhances the influence of ML by providing the confidence necessary for stakeholders to rely on ML-driven insights, ensuring that these technologies positively contribute to rational, evidence-based decisions.

Theoretical and Practical Implications

The acceptance of the hypotheses presents both theoretical and practical implications. Theoretically, the findings contribute to the literature by identifying trust serves as a key role in mediating the correlation between ML and RDM, particularly within the context of digital transformation. This underscores the significance of trust in successful technology adoption and integration, suggesting that future research could explore other potential mediators or moderators, such as organizational culture or user expertise, to further unravel the complex dynamics between ML and decision-making.

From a practical perspective, these results have significant implications for digital transformation efforts, particularly in the e-government sector in Jordan and beyond. Governments and organizations seeking to implement ML technologies must focus on building and maintaining trust, as it plays a key role in ensuring that decision-makers are willing to rely on machine learning insights. This could involve transparency in ML models, ensuring data security, and creating robust governance frameworks that foster trust in technological solutions.

The results delve into the comprehensive theoretical and practical implications of integrating machine learning (ML) into rational decision-making (RDM) within the context of Jordanian e-government. This discussion underscores how the study contributes to advancing the existing literature on e-government, ML, and decision-making by examining the roles of supervised and unsupervised machine learning models and exploring the essential role of trust as a mediator.

The findings emphasize the unique impacts of supervised and unsupervised ML in different phases of RDM, providing theoretical insights that expand the understanding of how these models can enhance decision-making processes in government institutions. This study's approach, which distinguishes the effects of supervised and unsupervised ML, clarifies their contributions to intelligence gathering, analysis and design, and the choice phase, offering future researchers a foundation to investigate how specific ML models may benefit various decision-making processes within governmental frameworks.

Furthermore, the empirical confirmation of trust as a significant mediator between ML and RDM is a critical theoretical contribution of this research. Trust has been recognized in literature as essential to effective decision-making and technology adoption, yet its role within ML-powered decision-making in e-government contexts has remained underexplored.

The study demonstrates that trust can enhance the impact of ML on decision-making, highlighting that when trust in ML is strong, its effectiveness is amplified, especially in the intelligence gathering and analysis and design phases of decision-making. This aligns with existing theories of trust in technology, reinforcing the need for trust-building practices in the public sector and suggesting that trust, as a mediator, plays a crucial role in achieving optimal ML integration. By expanding the literature on trust, this research supports further exploration into the strategies that build trust in AI and ML applications, contributing to both technology adoption studies and trust theory in digital transformation.

From a practical standpoint, this research illustrates how ML can be instrumental in improving the decision-making capabilities of public sector institutions by optimizing data collection and analysis. This is particularly important in the intelligence gathering phase, where ML enables more accurate and thorough data collection, providing middle-level management with clearer insights that inform rational decision-making.

For practical implementation, this indicates a need for targeted training programs aimed at empowering government employees, especially those less familiar with ML, to interpret and apply ML-driven insights in their daily roles. Such training not only bridges skill gaps but also encourages user engagement and understanding, which is vital for building confidence in technology-driven processes.

Trust emerges as a crucial element for practical implementation, with findings emphasizing that trust-building measures are necessary to drive ML adoption and ensure its effectiveness in decision-making. Transparency and security enhancements in ML systems are especially significant, as they can cultivate trust among employees and stakeholders. The study suggests practical strategies such as incorporating explainable AI features that allow users to understand how decisions are made, as well as maintaining open communication about data usage, processing, and storage.

By implementing these measures, government institutions can foster a higher level of trust in ML systems, creating an environment where decision-makers are more likely to rely on and value ML insights. This underscores the relevance of trust-building strategies within the practical sphere of digital governance, as a trusted ML system is more likely to be adopted and effectively utilized.

Moreover, this research offers practical implications for policy development within e-government. The study's findings suggest that policymakers need to consider establishing guidelines to govern the ethical and transparent use of ML in public administration. Developing such guidelines is essential for promoting responsible AI usage and for aligning ML applications with legal and ethical standards, which are particularly important in a public sector context.

Additionally, policies that explicitly address data handling and privacy protections are imperative, as these issues significantly impact trust and the broader acceptance of ML technologies within government entities. With effective policy structures in place, governmental institutions can foster a responsible and secure environment for ML integration, supporting digital transformation while preserving public trust.

In conclusion, the results demonstrate that trust has a significant mediating role in mediating the correlation between ML and RDM in digital transformation. Trust is a key factor that enhances the positive impact of ML on decision-making, either fully or partially mediating this relationship depending on the type of machine learning being employed.

These findings underscore the necessity for organizations, especially in e-government, to focus on trust-building strategies to maximize the benefits of ML-driven decision-making processes. These results are supported by similar claims from previous research (Araujo et al., 2020; Ryan, 2020; Ferrario et al., 2020). The study not only enhances the ongoing discussion surrounding ML, trust, and decision-making but also opens doors for future research to explore other dimensions of these relationships in the digital era. Also, table 42 presents a summary of the results for all the hypotheses tested in the study.

Table 42.

Summary of testing hypothesis

Hypothesis	Path	Standardized Coefficients		R^2	Sig	LLCI	ULCI	Accept/Reject
		Beta	T					
H1	SML → RDM	0.770	14.208	0.592	0.000	0.759	1.005	Accepted
H1a	SML → Int	0.749	13.314	0.560	0.000	0.706	0.952	Accepted
H1b	SML → Desig	0.611	9.098	0.373	0.000	0.625	0.973	Accepted
H1c	SML → Choi	0.668	10.569	0.446	0.000	0.842	1.230	Accepted
H2	UNSML → RDM	0.867	20.720	0.755 High	0.000	0.693	0.840	Accepted
H2a	UN ML → Int	0.811	16.348	0.658	0.000	0.607	0.774	Accepted
H2b	UNSML → Desig	0.807	16.106	0.651	0.000	0.712	0.912	Accepted
H2c	UNSML → Choi	0.688	11.181	0.474	0.000	0.677	0.967	Accepted
H3	ML→ Trust	0.917	27.018	0.840 High	0.000	0.823	0.953	Accepted
H3a	SML → Trust	0.795	15.425	0.631	0.000	0.7	0.91	Accepted
H3b	UNSML → Trust	0.862	20.004	0.742 High	0.000	0.605	0.737	Accepted
H4	Trust → RDM	0.949	35.643	0.901 V. High	0.000	1.02	1.13	Accepted
H4a	Trust → Int	0.876	21.393	0.767 High	0.000	0.869	1.046	Accepted
H4b	Trust → Desig	0.789	15.119	0.622	0.000	0.89	1.15	Accepted
H4c	Trust → Choi	0.840	18.220	0.705 High	0.000	1.15	1.43	Accepted

Summary

This chapter delves into the broader implications of the findings, particularly how ML contributes to improving RDM and fostering trust in e-government. It explores the importance of ML in the Jordanian context, its capacity to facilitate more informed decisions, and the necessity of trust as a mediator in the ML-RDM relationship. The discussion highlights how the study bridges existing gaps in the literature and opens new pathways for future research on ML, trust, and decision-making in e-government.

In sum, this chapter discussion emphasizes the significance of ML as a transformative tool for enhancing decision-making processes in government while also acknowledging that trust is pivotal to its successful integration. This research not only contributes theoretically by highlighting the roles of trust and specific ML models within the RDM phases but also provides actionable insights for the public sector. For future studies, these findings open pathways to explore further applications of ML within government and the impact of trust in fostering digital transformation initiatives. In practical terms, this research provides a foundation for government entities to implement ML responsibly and effectively, ultimately aiding in achieving more informed, efficient, and trustworthy governance.

CHAPTER VI

Conclusion and Recommendations

Artificial intelligence, particularly (ML), has proven its efficacy in multiple industries, revolutionizing processes and enhancing efficiency. The rise of ML, driven by advancements in data mining and big data, sophisticated algorithms, and improved processing power, is reshaping digital systems and exerting a profound influence on RDM. This transformation highlights the need for social sciences and information systems researchers to investigate how (ML) impacts decision-making processes. A thorough understanding of these implications is crucial for promoting academic development and practical progress in ML technologies.

This research highlights this critical need by examining the role of trust as a mediator in the correlation among ML and (RDM), by identifying key challenges and outlining future research opportunities. The following chapter presents the outcomes of this research, along with recommendations for practitioners and researchers to further explore and harness the potential of ML in decision-making contexts.

This research investigated the impact of (ML) on (RDM) within the context of digitalization initiatives. It examined how SML and UNSML contribute to decision-making processes in public administration. To analyze the influence of ML on RDM, five research hypotheses were developed, with trust playing a mediator role in this correlation. The multiple regression analysis conducted using SPSS indicated that ML significantly influences both trust and RDM in digitalization at e-government. Although these hypotheses primarily focus on the dynamics among ML, RDM, and trust mediation in e-government, their implications extend beyond this context. The insights derived from this study can enhance broader research on the application and effects of ML across diverse sectors. Additionally, exploring these relationships in various contexts and integrating other interaction variables may yield valuable findings for future research.

The findings demonstrated that supervised machine learning significantly improves middle management's decision-making capabilities by implementing better data analysis, problem identification, and the selection of appropriate solutions. SML enhances the accuracy and effectiveness of decisions, especially during the intelligence gathering, analysis design, and choice phases of the RDM. By delivering precise, data-driven insights, ML facilitates more informed RDM, which is essential in the rapidly changing digital environment of e-government. UNSML also proved valuable, particularly in identifying patterns and insights from unstructured or unlabeled data, contributing to improved decision-making in more complex scenarios. This ability to derive insights from large datasets further supports the role of ML as a transformative tool in public sector governance.

An important theme emerging from the study is the role of trust. Trust is critical in ensuring the adoption and effective use of ML systems in decision-making. The confidence in machine learning algorithms' transparency, security, and reliability was essential for government officials and stakeholders to embrace ML's potential fully.

In summary, the incorporation of machine learning in Jordan's e-government has shown great promise in enhancing decision-making processes. By fostering trust and transparency and by building the necessary infrastructure and technical capacity, machine learning can become a cornerstone in improving the efficiency and responsiveness of government services. This study delivers valuable knowledge for policymakers and technologists on harnessing ML's capabilities to achieve greater outcomes in the digital transformation of public governance.

Recommendations

Drawing from the research findings and the analysis provided in this thesis, several recommendations can be proposed to improve the use of ML in RDM processes during the digital transformation of Jordan's e-government.:

1. Enhance Trust in Machine Learning Systems

- Focus on Transparency and Explainability: To foster trust in ML systems, government agencies should prioritize making their decision-making processes transparent. This ensures that ML models can be easily explained to non-technical users and stakeholders, providing confidence in their outputs.
- Security Measures: Establish strong security protocols to safeguard sensitive government data and ensure the accuracy and reliability of machine learning (ML) systems. This will enhance trust in the system's decisions and recommendations.

2. Continuous Training and Capacity Building

- Develop Training Programs: Regular training programs targeted at middle-level management in e-government are needed. These programs should enhance their understanding of SML and UNSML models, focusing on practical applications and ethical considerations.

- Increase Technical Skills: To effectively implement ML technologies, building technical expertise among employees is essential. This can be achieved through collaboration with educational institutions and the private sector to offer specialized training courses in ML and AI technologies.

3. Adopt a Phased ML Implementation Approach
   - Begin with Pilot Projects: Implement ML in specific, less complex government tasks as pilot projects. This will allow for learning and adaptation without disrupting essential services. Gradually, as expertise grows, ML systems can be scaled across more critical and complex government functions.
   - Use Case-Specific Customization: Different government departments may have unique needs for ML. Therefore, it is recommended that ML models be tailored to fit each department's specific requirements to ensure optimal performance and utility.
4. Strengthen Data Infrastructure
   - Invest in Data Infrastructure: Developing a robust data infrastructure is vital for effective ML integration. E-government services should focus on improving data collection, storage, and processing capabilities to ensure ML systems have access to accurate and up-to-date information, leading to better decision-making outcomes.
   - Data Standardization: Standardizing data formats across government agencies will facilitate the efficient use of ML algorithms and improve the interoperability of different systems.
5. Focus on Ethical Considerations and Governance
   - Establish Ethical Guidelines for ML Use: Governments should establish clear ethical guidelines that govern the use of ML, especially in sensitive areas such as law enforcement and healthcare. These guidelines should address fairness, bias, and accountability in ML-driven decision-making processes.
   - Governance Frameworks for ML Systems: Implement governance frameworks that regularly monitor and evaluate the performance of ML systems. These frameworks should ensure that ML technologies are used responsibly and in alignment with legal and ethical standards.
6. Improve Public Awareness and Engagement
   - Public Awareness Campaigns: To increase the acceptance of ML technologies in e-government, public awareness campaigns should be launched to inform

citizens about the benefits, limitations, and safeguards. This will help reduce resistance to adopting new technologies and build trust in e-government services.

- Incorporate Public Feedback: Engage citizens in the ML implementation process by incorporating their feedback into the development and refinement of ML-driven services. This will create a more inclusive approach to digital transformation.

7. Support Ongoing Research and Innovation

- Collaborate with Academia and Industry: Foster collaborations between government, academia, and the private sector to drive ongoing research and innovation in ML applications.
- Encourage Pilot Programs and Trials: Promote further research and pilot programs to explore new ML use cases and identify potential risks or limitations. This can offer important insights into the practical application of ML technologies within different areas of public service.

If implemented, these recommendations will help the Jordanian e-government harness the great potential of machine learning technologies, leading to improved decision-making processes, enhanced trust, and a more efficient and transparent government system.

Recommendations According to Findings

The research’s findings highlight the essential role of trust as a mediator in the correlation between (ML) and (RDM) within the context of Jordan's e-government transformation. To foster greater trust in ML systems, transparency and security measures must be prioritized. This includes implementing explainable AI to clarify decision-making processes and strengthening data security to alleviate concerns over data privacy. Ensuring that ML systems are transparent and secure will increase trust among government employees and the public.

Capacity building is essential for middle-level management, who are crucial in utilizing ML technologies for decision-making. Targeted training programs that focus on both supervised and unsupervised ML can help managers effectively integrate these tools into their decision-making processes.

Additionally, pilot programs that introduce ML gradually will allow for a smoother transition, enabling managers to experience the benefits before wider adoption. Optimizing data infrastructure to support advanced data collection and analysis is also crucial for improving ML's effectiveness in government decision-making.

Ethical considerations, including fairness, accountability, and transparency, must be addressed to ensure responsible ML use. Ethical guidelines for deploying ML in decision-making should be established, and ongoing audits should be conducted to maintain fairness and prevent algorithmic bias. Expanding research on ML's role in decision-making across various sectors and exploring other potential mediators, such as organizational culture, will contribute to a deeper understanding of how ML can transform decision-making processes in different contexts.

Limitations and Recommendations for Further Research

Despite providing valuable insights into the role of machine learning (ML) in rational decision-making (RDM) within digital transformation contexts, this study has some limitations can be improved in future research. First, the study’s focus on trust as the primary mediating variable which can be expanded in future to other influential factors, such as organizational culture, employee expertise, and technology adoption readiness, which may also play critical roles in shaping the relationship between ML and decision-making.

The study’s scope was further restricted to the e-government sector, meaning that findings may not generalize to other sectors like healthcare, finance, or education, where the dynamics of ML adoption and trust in decision-making could vary. Additionally, the study’s cross-sectional design provides only a snapshot of ML’s impact on RDM, leaving room for future longitudinal studies to examine how this relationship evolves over time and across technology advancements.

Ethical considerations, such as fairness and accountability, were also not examined in-depth, suggesting that governance frameworks and regulatory mechanisms should be explored further to ensure responsible and unbiased ML deployment. These limitations underscore the need for continued research to develop a more holistic understanding of how ML influences decision-making across diverse organizational settings and over time.

Expanding on the findings and insights of this research, various recommendations for future research can be suggested to enhance the understanding of (ML) and its influence on (RDM) in the context of digital transformation initiatives:

first is exploring other mediating variables: While this study focused on trust as a key mediator between dependent and independent variables, future research should investigate additional mediating or moderating variables. Factors such as organizational culture, employee expertise, and technology adoption readiness may also influence the relationship between ML and decision-making. Understanding these dynamics can provide a more comprehensive picture of how ML impacts decision-making in different organizational contexts.

Second, Sector-Specific Studies**:** Further research should be conducted across various sectors beyond e-government, such as healthcare, education, and finance. Investigating how ML and trust interact in these industries will help identify sector-specific challenges and opportunities for leveraging ML in decision-making. Comparative studies across sectors could reveal patterns and unique considerations relevant to each industry's digital transformation journey.

Third, Longitudinal Studies on ML Adoption: Given the evolving nature of ML technologies, longitudinal studies are recommended to track the long-term effects of ML on decision-making processes. Research that spans several years will provide valuable insights into how trust in ML systems evolves over time, the sustainability of decision-making improvements, and the impact of technological advancements on RDM in various governmental and organizational settings.

Finally, Ethical Considerations and Governance Models: Future research should further investigate the ethical barriers to using ML in decision-making, particularly issues related to fairness, bias, and accountability. Developing governance models that ensure ethical deployment and continuous monitoring of ML systems will be crucial as governments and organizations increasingly rely on these technologies. Research in this area could explore frameworks for ethical audits and regulatory mechanisms tailored to ML in public administration.

By exploring these areas, future research can offer a deeper and more nuanced awareness of the influence of ML technologies on RDM phases and the role they play in cultivating trust within diverse governmental and digital transformation contexts.

Summary

The conclusion reiterates the significant impact of ML on RDM in Jordan's e-government, particularly through the mediation of trust. It offers practical recommendations for improving ML adoption, such as enhancing transparency and explain ability of ML systems, investing in technical training for government employees, and focusing on ethical considerations. The chapter also suggests that ML should be implemented gradually through pilot projects and stresses the need for robust data infrastructure to support ML-driven decision-making in the public sector.

References

Abu-Shanab, E. (2014). Antecedents of trust in e-government services: an empirical test in Jordan. Transforming Government: People, Process and Policy, 8(4), 480-499. https://doi.org/10.1108/TG-08-2013-0027.

Acciarini, C., Brunetta, F., & Boccardelli, P. (2021). Cognitive biases and decision-making strategies in times of change: a systematic literature review. Management Decision, 59(3), 638-652. https://doi.org/10.1108/MD-07-2019-1006

Acosta, S. M., & Sant'Anna, A. M. O. (2022). Machine learning-based control charts for monitoring fraction nonconforming product in smart manufacturing. International Journal of Quality & Reliability Management.

Adadi, A., & Berrada, M. (2018). Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI). IEEE Access, 6, 52138-52160.

Al-A'wasa, S. I. S. (2018). The impact of organizational justice on the counterproductive work behavior (CWB): A field study conducted in the Jordan Customs Department (JCD). International Journal of Business and Social Science, 9(1), 27-38.

Alexopoulos, C., Lachana, Z., Androutsopoulou, A., Diamantopoulou, V., Charalabidis, Y., & Loutsaris, M. A. (2019, April). How machine learning is changing e-government. In Proceedings of the 12th International Conference on Theory and Practice of Electronic Governance (pp. 354-363).

Alkhwaldi, A., Kamala, M., & Qahwaji, R. (2017, December). From e-government to cloud-government: Challenges of Jordanian citizens' acceptance for public services. In 2017 12th International Conference for Internet Technology and Secured Transactions (ICITST) (pp. 298-304). IEEE.

Alloghani, M., Al-Jumeily, D., Mustafina, J., Hussain, A., & Aljaaf, A. J. (2020). A systematic review on supervised and unsupervised machine learning algorithms for data science. Supervised and unsupervised learning for data science, 3-21.

Al-Mushayt, O. S. (2019). Automating E-Government services with artificial intelligence. IEEE Access, 7, 146821-146829.

Al-Nawasrah, A., Al-Hmouz, R., & Hmoud, A. (2020). E-government service quality in Jordan: A citizen perspective. Information Development, 36(1), 59-72.

Alomari, M., Qawasmeh, O., & Aljarah, I. (2018). The Impact of Big Data and Artificial Intelligence on E-Government: The Case of Jordan. In Proceedings of the 2018 2nd International Conference on Cloud and Big Data Computing (pp. 37-41). Association for Computing Machinery.

Androutsopoulou, A., Karacapilidis, N., Loukis, E., & Charalabidis, Y. (2019). Transforming the communication between citizens and government through AI-guided chatbots. Government Information Quarterly, 36(2), 358-367.

Araujo, T., Helberger, N., Kruikemeier, S., & De Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. AI & society, 35, 611-623.

Argyris, C., & Schön, D. A. (1997). Organizational learning: A theory of action perspective. Reis, (77/78), 345-348.

Bader, V., & Kaiser, S. (2019). Algorithmic decision-making? The user interface and its role for human involvement in decisions supported by artificial intelligence. Organization, 26(5), 655-672.

Bag, S., Gupta, S., Kumar, A., & Sivarajah, U. (2021). An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance. Industrial Marketing Management, 92, 178-189.

Bedué, P., & Fritzsche, A. (2022). Can we trust AI? An empirical investigation of trust requirements and guide to successful AI adoption. Journal of Enterprise Information Management, 35(2), 530-549.

Bell, D. E. (1982). "Regret in Decision Making under Uncertainty." Operations Research.

Benthall, S., & Haynes, B. D. (2019, January). Racial categories in machine learning. In Proceedings of the conference on fairness, accountability, and transparency (pp. 289-298).

Binmore, K., & Nalebuff, B. (1992). The Foundations of Game Theory.

Bokhari, S. A. A., & Myeong, S. (2022). Use of artificial intelligence in smart cities for smart decision-making: A social innovation perspective. Sustainability, 14(2), 620.

Breiman, L. (2017). Classification and regression trees. Routledge.

Broby, D., The use of predictive analytics in finance. The Journal of Finance and Data Science 2022, 8, pp.145-161.

Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. Technovation, 106, 102312.

Creswell, J. W. (2009). Research Design: Qualitative, Quantitative and Mixed Approaches. Research Design: Qualitative, Quantitative, and Mixed Methods Approaches (3rd ed.). London: SAGE

Dasgupta, A., & Nath, A. (2016). Classification of machine learning algorithms. International Journal of Innovative Research in Advanced Engineering (IJIRAE), 3(3), 6-11.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). Technology acceptance model. J Manag Sci, 35(8), 982-1003.

de Sousa, W. G., de Melo, E. R. P., Bermejo, P. H. D. S., Farias, R. A. S., & Gomes, A. O. (2019). How and where is artificial intelligence in the public sector going? A literature review and research agenda. Government Information Quarterly, 36(4), 101392.

Djafri, L. (2022). Dynamic Distributed and Parallel Machine Learning algorithms for big data mining processing. Data Technologies and Applications, 56(4), 558-601.

Doshi-Velez, F., & Kim, P. (2017). "Towards a rigorous science of interpretable machine learning." Proceedings of the 34th International Conference on Machine Learning.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International journal of information management, 48, 63-71.

El Naqa, I.; Murphy, M. J. What Are Machine and Deep Learning? In Machine and Deep Learning in Oncology, Medical Physics and Radiology; Springer

International Publishing: Springer: Berlin/Heidelberg, Germany,2022; pp.3-15.

Elsner, W. (1989). Adam Smith's model of the origins and emergence of institutions: the modern findings of the classical approach. Journal of Economic issues, 23(1), 189-213.

Ferrario, A., Loi, M., & Viganò, E. (2020). In AI we trust incrementally: A multi-layer model of trust to analyze human-artificial intelligence interactions. Philosophy & Technology, 33, 523-539.

Ghimire, A., Thapa, S., Jha, A. K., Adhikari, S., & Kumar, A. (2020, October). Accelerating Business Growth with Big Data and Artificial Intelligence. In 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC) (pp. 441-448). IEEE.

Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. Annual review of psychology, 62(1), 451-482.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). Multivariate Data Analysis (7th ed.). Harlow, UK: Pearson Education Limited.

Halaweh, M. (2018). Artificial intelligence government (Gov. 3.0): The UAE leading model. Journal of Artificial Intelligence Research, 62, 269-272.

Hinkin, T. R. (1998). A brief tutorial on the development of measures for use in survey questionnaires. Organizational Research Methods, 2(1), 104–121.

Hwang, C. L., & Yoon, K. (1981). Multiple Attribute Decision Making: Methods and Applications.

Ingrams, A., Kaufmann, W., & Jacobs, D. (2022). In AI we trust? Citizen perceptions of AI in government decision making. Policy & Internet, 14(2), 390-409.

Janssen, M., Brous, P., Estevez, E., Barbosa, L. S., & Janowski, T. (2020). Data governance: Organizing data for trustworthy Artificial Intelligence. Government Information Quarterly, 37(3), 101493.

Janssen, M., Hartog, M., Matheus, R., Yi Ding, A., & Kuk, G. (2022). Will algorithms blind people? The effect of explainable AI and decision-makers' experience on AI-supported decision-making in government. Social Science Computer Review, 40(2), 478-493.

Jiang, T., Gradus, J. L., & Rosellini, A. J. (2020). Supervised machine learning: a brief primer. Behavior therapy, 51(5), 675-687.

Julmi, C. (2019). When rational decision-making becomes irrational: a critical assessment and re-conceptualization of intuition effectiveness. Business Research, 12(1), 291-314

Kahneman, D., & Tversky, A. (2013). Prospect theory: An analysis of decision under risk. In Handbook of the fundamentals of financial decision making: Part I (pp. 99-127).

Karatas, I., & Budak, A. (2022). Development and comparative of a new meta-ensemble machine learning model in predicting construction labor productivity. Engineering, Construction and Architectural Management, (ahead-of-print).

Keeney, R. L., & Raiffa, H. (1993). Decisions with multiple objectives: preferences and value trade-offs. Cambridge university press.

Khodabandehlou, S., & Zivari Rahman, M. (2017). Comparison of supervised machine learning techniques for customer churn prediction based on analysis of customer behavior. Journal of Systems and Information Technology, 19(1/2), 65-93.

Kothari, C. R. (2013). Research Methodology: Methods and Techniques, New Age International (P) Limited, Publishers, 2013

Kumar, A., & Kalse, A. (2021). Usage and adoption of artificial intelligence in SMEs. Materials Today: Proceedings.

Kureljusic, M., & Metz, J. (2023). The applicability of machine learning algorithms in accounts receivables management. Journal of Applied Accounting Research.

Lantz, B. (2021). Overview of Machine Learning Tools. In The Machine Age of Customer Insight. Emerald Publishing Limited

Liu, B. (2021). In AI we trust? Effects of agency locus and transparency on uncertainty reduction in human–AI interaction. Journal of computer-mediated communication, 26(6), 384-402.

Loewenstein, G., & Lerner, J. S. (2003). "The Role of Affect in Decision Making." In Handbook of Affective Science.

Loomes, G., & Sugden, R. (1982). Regret theory: An alternative theory of rational choice under uncertainty. The economic journal, 92(368), 805-824.

Loukili, M.; Messaoudi, F.; El Ghazi, M. Machine learning based recommender system for e-commerce. IAES International Journal of Artificial Intelligence 2023, 12(4), pp.1803-1811.

Lu, D., Ding, Y., Asian, S., & Paul, S. K. (2018). From Supply Chain Integration to Operational Performance: The Moderating Effect of Market Uncertainty. Global Journal of Flexible Systems Management, 19(7), 3–20.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. Academy of management review, 20(3), 709-734.

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). "Developing and Validating Trust Measures for e-Commerce: An Integrative Typology." Information Systems Research.

Merkert, J., Mueller, M., & Hubl, M. (2015). A survey of the application of machine learning in decision support systems.

Ministry of Digital Economy and Entrepreneurship (Jordan). (2022). National Digital Transformation Strategy 2022-2025. Amman, Jordan: Ministry of Digital Economy and Entrepreneurship.

Nielsen, S. (2022). Management accounting and the concepts of exploratory data analysis and unsupervised machine learning: a literature study and future directions. Journal of Accounting & Organizational Change, 18(5), 811-853.

Nortje, M. A., & Grobbelaar, S. S. (2020, June). A Framework for the Implementation of Artificial Intelligence in Business Enterprises: A Readiness Model. In 2020 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC) (pp. 1-10). IEEE.

Nutt, P. C. (2007). Intelligence gathering for decision making. Omega, 35(5), 604-622.

Ongena, Y. P., Haan, M., Yakar, D., & Kwee, T. C. (2020). Patients' views on the implementation of artificial intelligence in radiology: development and validation of a standardized questionnaire. European radiology, 30, 1033-1040.

Osborne, M. J., & Rubinstein, A. (1994). A Course in Game Theory.

Oumkaltoum, B., & Mahmoud, E. B. M. (2019, October). Business Intelligence and EDA Based Architecture for Interoperability of E-Government Data Services. In 2019 IEEE International Smart Cities Conference (ISC2) (pp. 402-407). IEEE.

Paliukas, V., & Savanevičienė, A. (2018). Harmonization of rational and creative decisions in quality management using AI technologies. Economics and business, 32(1), 195-208.

Pereira, G. V., Macadar, M. A., Luciano, E. M., & Testa, M. G. (2017). Delivering public value through open government data initiatives in a Smart City context. Information Systems Frontiers, 19(2), 213-229.

Piscopo, A., Siebes, R., & Hardman, L. (2017). Predicting sense of community and participation by applying machine learning to open government data. Policy & Internet, 9(1), 55-75.

Power, D. J., Cyphert, D., & Roth, R. M. (2019). Analytics, bias, and evidence: The quest for rational decision making. Journal of Decision Systems, 28(2), 120-137.

Powers, D. M. (2020). Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation.

Pugliese, R.; Regondi, S. ; Marini, R. Machine learning-based approach: global trends, research directions, and regulatory standpoints. Data Science and Management 2021, 4, 19-29. [CrossRef]

Qasem, A. A., Alkafaween, E., & Jaradat, R. (2021). Machine learning for enhancing Jordanian e-government services: A case study of chatbots. Journal of Information Technology Management, 32(2), 44-61.

Raschka, S., & Mirjalili, V. (2019). Python machine learning: Machine learning and deep learning with Python, scikit-learn, and TensorFlow 2. Packt Publishing Ltd.

Reshi, Y. S., & Khan, R. A. (2014). Creating business intelligence through machine learning: An Effective business decision making tool. In Information and Knowledge Management (Vol. 4, No. 1, pp. 65-75).

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?" Explaining the predictions of any classifier. In Proceedings of the 22nd

ACM SIGKDD international conference on knowledge discovery and data mining (pp. 1135-1144).

Robinson, J., & Dow, S. (2021). Economic philosophy. Routledge.

Rubinstein, A. (1998). Modeling bounded rationality. MIT press.

Ryan, M. (2020). In AI we trust: ethics, artificial intelligence, and reliability. Science and Engineering Ethics, 26(5), 2749-2767.

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial least squares structural equation modeling. Handbook of market research, 26(1), 1-40.

Satti, J. A., & Rasool, S. W. Exploring the Role of Technology in Enhancing Government Transparency and Accountability. Harf-o-Sukhan, 2024, 8(2), 621-633.

Schmidt, P., Biessmann, F., & Teubner, T. (2020). Transparency and trust in artificial intelligence systems. Journal of Decision Systems, 29(4), 260-278.

Schwalb, J., Menon, V., Tenhundfeld, N., Weger, K., Mesmer, B., & Gholston, S. (2022, November). A Study of Drone-based AI for Enhanced Human-AI Trust and Informed Decision Making in Human-AI Interactive Virtual Environments. In 2022 IEEE 3rd International Conference on Human-Machine Systems (ICHMS) (pp. 1-6). IEEE.

Scott, S. G., & Bruce, R. A. (1995). Decision-making style: The development and assessment of a new measure. Educational and psychological measurement, 55(5), 818-831.

Sekaran, U., & Bougie, R. (2016). Research Methods for Business: A Skill-Building Approach (7th ed.). Chichester, West Sussex, UK: Wiley & Sons Ltd.

Sen, P.C.; M. Hajra; Ghosh, M. Supervised Classification Algorithms in Machine Learning: A Survey and Review. In Emerging Technology in Modelling and Graphics: Proceedings of IEM Graph, Singapore (2020). [CrossRef]

Sharma, G. D., Yadav, A., & Chopra, R. (2020). Artificial intelligence and effective governance: A review, critique and research agenda. Sustainable Futures, 2, 100004.

Simon, H. A. (1979). Rational decision making in business organizations. The American economic review, 69(4), 493-513.

Simon, H. A. (1990). Bounded rationality. Utility and probability, 15-18.

Simon, H. A., Dantzig, G. B., Hogarth, R., Plott, C. R., Raiffa, H., Schelling, T. C., ... & Winter, S. (1987). Decision making and problem solving. Interfaces, 17(5), 11-31.

Spicer, D. P., & Sadler-Smith, E. (2005). An examination of the general decision making style questionnaire in two UK samples. Journal of Managerial Psychology, 20(2), 137-149.

Stirati, A. (1994). The theory of wages in classical economics: a study of Adam Smith, David Ricardo, and their contemporaries. Edward Elgar Publishing.

Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. Government Information Quarterly, 36(2), 368-383.

Thaler, R. H., & Sunstein, C. R. (2009). Nudge: Improving decisions about health, wealth, and happiness. Penguin.

Usama, M.; Qadir, J.; Raza, A. ; Arif, H.; Yau, K. l. A. Y. Elkhatib, K. l. A.; Hussain, A.; Al-Fuqaha, A.; Unsupervised Machine Learning for Networking: Techniques, Applications and Research Challenges. IEEE Access, 2019, 7, 65579-65615. [CrossRef]

Uzonwanne, F. C. (2023). Rational model of decision-making. In Global encyclopedia of public administration, public policy, and governance (pp. 11230-11235). Cham: Springer International Publishing.

Varma, R., Verma, Y., Vijayvargiya, P., & Churi, P. P. (2021). A systematic survey on deep learning and machine learning approaches of fake news detection in the pre-and post-COVID-19 pandemic. International Journal of Intelligent Computing and Cybernetics, 14(4), 617-646.

Vrbka, J., & Rowland, Z. (2020). Using artificial intelligence in company management. In Digital Age: Chances, Challenges and Future 7 (pp. 422-429). Springer International Publishing.

Wang, J.; Ma, Y.; Zhang, L.; Gao, R. X.; Wu, D. Deep learning for smart manufacturing: Methods and applications. Journal of Manufacturing Systems 2018, 48, 144-156. [CrossRef]

Weick, K. E. (1995). Sense-making in organizations (Vol. 3). Sage.

Wiener, N. (2019). Cybernetics or Control and Communication in the Animal and the Machine. MIT press.

Wirtz, B. W., & Müller, W. M. (2019). An integrated artificial intelligence framework for public management. Public Management Review, 21(7), 1076-1100.

World Bank. (2021). Jordan Digital Economy Diagnostic. Washington, DC: World Bank Group.

APPENDEX A / QUESTIONNAIRE

Title: Assessing the Impact of Using Machine Learning on Rational Decision Making in Digital Transformation

Case study: e-government at Jordan

This Survey Questionnaire is to be filled out by e-government employees in Jordan, it could take (15-20 minutes from your valuable time).

Dear Prospective participant,

I am Ayat Salem, Ph.D. candidate at the Business Administration department, University of Near East, Northern Cyprus, working toward a doctorate degree in Business Administration. This questionnaire aims to determine the influences of using machine learning techniques (Supervised and Unsupervised learning) on rational decision-making in the digital transformation process at the Jordanian e-government. Let me emphasize that your participation in this study is voluntary. Please be assured that all information you provide will be kept strictly confidential and it will be used just for scientific research. Please indicate your level of agreement with the statements given below with five scales. Your participation represents a valuable contribution to this research. I want to thank you very much in advance for your cooperation and I hope that will serve the scientific research and help you in developing your government institution.

Sincerely yours,

Ayat Mohammad Salem

University of Near East, Department of Business Administration

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To be able to answer the questionnaire below and before filling the statements you have to know the below definition:

1- Supervised Machine Learning: is a subcategory of machine learning and artificial intelligence. It is defined by its use of labelled datasets to train algorithms that to classify data or predict outcomes accurately.
2- Unsupervised Machine Learning: is a subcategory of machine learning and artificial intelligence. It is useful in finding underlying patterns and relationships within unlabeled, raw data.

Section A: Demographics Profile:

Age: What is your age?

- ☐ 18-24 years' old
- ☐ 25-34 years' old
- ☐ 35-44 years' old
- ☐ 45-54 years' old
- ☐ 55-64 years' old
- ☐ 65- and above years' old

Education:

- ☐ High school graduate, diploma or the equivalent
- ☐ Associate degree
- ☐ Bachelor's degree
- ☐ Master's degree
- ☐ Doctorate degree

Experience period:

- ☐ 0-3 years
- ☐ 4-7 years
- ☐ 8-11 years
- ☐ 12-15 years
- ☐ 16 years and above

Gender:

- ☐ Male
- ☐ Female

Instructions: Sections (B-C) have (46) statements, for each statement, please indicate your level of agreement or disagreement on a scale of 1 to 5, where 1 represents "Strongly Disagree" and 5 represents "Strongly Agree."

Section B: Rational Decision-making. Dependent variable.

Q 1. I double-check my information sources to be sure I have the right facts before making decisions.

1	2	3	4	5

Q 2. I make decisions in a logical and systematic way.

1	2	3	4	5

Q 3. My decision making requires careful thought.

1	2	3	4	5

Q 4. When making a decision, I consider various options in terms of a specified goal.

1	2	3	4	5

Q 5. I usually have a rational basis for making decisions.

1	2	3	4	5

Q 6. In my opinion, local government uses new technologies rather than using old methods for decision-making regarding the digital transformation.

1	2	3	4	5

Q 7. In my opinion, local government gathers lot of data on any opportunity that arises to decide better for the digital transformation.

1	2	3	4	5

Q 8. In my opinion, whenever local government face a difficult situation, it is optimistic about finding a good solution for the digital transformation.

1	2	3	4	5

Q 9. In my opinion, my local government does not delay decision-making for the digital transformation when- ever it needed before it is too late.

1	2	3	4	5

Q 10. In my opinion, local government considers all the available alternatives for decision-making regarding the digital transformation.

1	2	3	4	5

Section C-1: Machine Learning (Supervised Learning). Independent variable

Q 11. The use of supervised machine learning improves the accuracy of data analysis

1	2	3	4	5

Q 12. Supervised machine learning enhances the identification and understanding of relevant variables and patterns.

1	2	3	4	5

Q 13. Using supervised machine learning enables more efficient and effective data gathering.

1	2	3	4	5

Q 14. Supervised machine learning facilitates the discovery of valuable.

1	2	3	4	5

Q 15. The use of supervised machine learning improves the quality and reliability of information used.

1	2	3	4	5

Q 16. Supervised machine learning aids in identifying the optimal decision alternative among available options.

1	2	3	4	5

Q 17. The use of supervised machine learning improves the accuracy and speed of evaluating decision alternatives.

1	2	3	4	5

Q 18. Supervised machine learning enhances the assessment of potential consequences and risks associated with decision alternatives.

1	2	3	4	5

Q 19. Using supervised machine learning improves the ability to incorporate preferences and priorities in the decision-making process.

1	2	3	4	5

Q 20. The use of supervised machine learning facilitates the documentation and justification and outcomes

1	2	3	4	5

Q 21. Supervised machine learning helps in formulating comprehensive decision alternatives.

1	2	3	4	5

Q 22. The use of supervised machine learning assists in identifying and evaluating potential risks and uncertainties.

1	2	3	4	5

Q 23. Supervised machine learning enhances the generation and evaluation of decision criteria.

1	2	3	4	5

Q 24. Using supervised machine learning improves the ability to simulate and predict the outcomes of decision alternatives.

1	2	3	4	5

Q 25. The use of supervised machine learning facilitates the identification of trade-offs and dependencies among decision alternatives.

1	2	3	4	5

Section C-2: Machine Learning (Unsupervised Learning). Independent variable

Q 26. The use of unsupervised machine learning improves the accuracy of data analysis.

1	2	3	4	5

Q 27. Unsupervised machine learning enhances the identification and understanding of relevant variables and patterns.

1	2	3	4	5

Q 28. Using unsupervised machine learning enables more efficient and effective data gathering.

1	2	3	4	5

Q 29. Unsupervised machine learning facilitates the discovery of valuable insights

1	2	3	4	5

Q 30. The use of unsupervised machine learning improves the quality and reliability of information used.

1	2	3	4	5

Q 31. Unsupervised machine learning aids in identifying the optimal decision alternative among available options during Rational Design Making.

1	2	3	4	5

Q 32. The use of unsupervised machine learning improves the accuracy and speed of evaluating decision alternatives.

1	2	3	4	5

Q 33. Unsupervised machine learning enhances the assessment of potential consequences and risks associated with decision alternatives.

1	2	3	4	5

Q 34. Using unsupervised machine learning improves the ability to incorporate preferences and priorities in the decision-making process.

1	2	3	4	5

Q 35. The use of unsupervised machine learning facilitates the documentation and justification of decision-making processes and outcomes.

1	2	3	4	5

Q 36. Unsupervised machine learning helps in formulating comprehensive decision alternatives during Rational Design Making.

1	2	3	4	5

Q 37. The use of unsupervised machine learning assists in identifying and evaluating potential risks and uncertainties during Rational Design Making.

1	2	3	4	5

Q 38. Unsupervised machine learning enhances the generation and evaluation of decision criteria during Rational Design Making.

1	2	3	4	5

Q 39. Using unsupervised machine learning improves the ability to simulate and predict the outcomes of decision alternatives during Rational Design Making.

1	2	3	4	5

Q 40. The use of unsupervised machine learning facilitates the identification of trade-offs and dependencies among decision alternatives during Rational Design Making.

1	2	3	4	5

Section D: Trust as the mediating variable

Q 41. In general, machine-learning technology is trusted nowadays.

1	2	3	4	5

Q42. I trust the accuracy and reliability of machine learning technologies for digital transformation decisions.

1	2	3	4	5

Q 43. I trust that machine learning technologies can effectively support rational decision-making processes in digital transformation.

1	2	3	4	5

Q 44. I feel confident in using machine learning technologies for decision-making tasks in digital transformation.

1	2	3	4	5

Q 45. I believe that machine learning technologies can provide valuable insights and recommendations for rational decision-making in digital transformation.

1	2	3	4	5

Q 46. I have a positive perception of the benefits that machine learning technologies bring to decision-making processes in digital transformation.

1	2	3	4	5

Thank you for your participation.

APPENDEX B / APPROVAL

NEAR EAST UNIVERSITY

SCIENTIFIC RESEARCH ETHICS COMMITTEE

09.10.2023

Dear Ayat Mohammad Abed Alkareem Salem

Your application titled **"Assessing The Impact of Using Machine Learning on Rational Decision Making in Digital Transformation Case study: e-government at Jordan"** with the application number NEU/SS/2023/1661 has been evaluated by the Scientific Research Ethics Committee and granted approval. You can start your research on the condition that you will abide by the information provided in your application form.

Prof. Dr. Aşkın KİRAZ

The Coordinator of the Scientific Research Ethics Committee

YAKIN DOĞU ÜNİVERSİTESİ
İKTİSADİ VE İDARİ BİLİMLERİ FAKÜLTESİ
NEAR EAST UNIVERSITY
FACULTY OF ECONOMICS AND ADMINISTRATIVE SCIENCES

Ministry of Digital Economy and Entrepreneurship
8th Circle Bayader Wadi Al Seer
P.O.Box 9903 Amman 11191 Jordan

13th October 2023

Re: Permission to conduct research at the Ministry of Digital Economy and Entrepreneurship

Dear Sir/Madam

I am Prof.Dr.Şerife Eyüpoğlu from Near East University, North Cyprus. My PhD student Ayat Salem is conducting research for her dissertation entitled "Assessing The Impact of Using Machine Learning on Rational Decision Making in Digital Transformation Case Study: E-Government in Jordan" and I am acting as her dissertation supervisor. It is in this respect that I am seeking permission to conduct our research at your ministry.

If permission is granted the research will entail collecting data from the employees (middle level management) through a questionnaire. The employees will be invited to participate, voluntarily, in the research, and the ones who agree to participate will be asked to complete a questionnaire that will distributed by Ms. Ayat Salem on the premises of the ministry. The completion of the questionnaire will take 10 to 15 minutes and participant responses will be kept confidential. Individual privacy will be maintained in all published and written data resulting from the research.

I therefore request permission to.conduct the research. Please let me know if you require any further information. I look forward to your response as soon as it is convenient.

Your sincerely

NEAR EAST UNIVERSITY
FACULTY OF ECONOMICS AND ADMINISTRATIVE SCIENCES
DEAN'S OFFICE
1988

Prof.Dr.Şerife Eyüpoğlu
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Near East University
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Ayat Salem
Department of Business Administration
Near East University
20204537@std.neu.edu.tr

وزارة الاقتصاد الرقمي والريادة

Date : 25-10-2023

Outgoing Number : 2023/8938

Dear Prof.Dr. Serife Eyupoglu

Subject: collection of data from employees

We are pleased to inform you that the Ministry of Digital Economy and Entrepreneurship of Jordan welcomes the opportunity to support your student Ms. Ayat Salem in her Ph.D. study "Assessing the impact of using machine learning on rational decision making in digital transformation. Case Study: E-government of Jordan".

through distributing the required questionnaire to MoDee's employees.

Yours Sincerely,

Sameera Mohammad Al-Zoubi

2023-10-25

Secretary General for Administrative & Financial Affairs

The Hashemite kingdom of Jordan
Ministry of Digital Economy and Entrepreneurship

APPENDEX C / PLAGIARISM REPORT
Turnitin Similarity Report

ASSESSING THE IMPACT OF USING MACHINE LEARNING ON RATIONAL DECISION MAKING IN DIGITAL TRANSFORMATION CASE STUDY: E-GOVERNMENT AT JORDAN By Ayat Salem 20204537

ORIGINALITY REPORT

12%	7%	7%	5%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Yakın Doğu Üniversitesi Student Paper	3%
2	www.mdpi.com Internet Source	2%
3	"Artificial Intelligence (AI) and Finance", Springer Science and Business Media LLC, 2023 Publication	1%
4	repository.ju.edu.et Internet Source	1%
5	docs.neu.edu.tr Internet Source	<1%
6	stmlportal.net Internet Source	<1%
7	Ayat Mohammad Salem, Serife Zihni Eyupoglu, Mohammad Khaleel Ma'aitah. "The Influence of Machine Learning on Enhancing	<1%

Appendix D
Curriculum Vitae

Eng. Ayat Mohammad Salem
Ph.D., MSc Business, Computer Engineer, PMP, CTM, CTAL-TA.
Email: ayat.salem@icloud.com
Mobile : +962785347547

Digital Transformation and Quality Management Consultant, with Computer Engineering bachelor's degree, e-Business master's, and **Ph.D. in e-Business Administration - management using Artificial Intelligence techniques.** I am a Project management professional PMP® certified since 2017, During **(13) years of experiences** in **management and consultation of digital transformation** working in public **and government sectors, private organizations, and NGOs**; I deal with mega projects, manage matrix organizations teams, and provide consulting services.

EDUCATION

- **Ph.D. Candidate of Business Administration**
  Near East University – Graduate School of Social Sciences,
  Cyprus –Nicosia 2020-2024.
- **Master degree in e-Business Administration with Excellent grade**
  Al-Balqa Applied University – Faculty of Finance and Managerial Sciences
  Amman – Jordan, January 2017.
- **Bachelor degree in Computer Engineering with Very Good grade**
  Al-Balqa Applied University– Faculty of Engineering Technology,
  Amman – Jordan, June 2009.
- **Scored 94.9% in the General Secondary Exams**
  Academic-Scientific August 2004.

EXPERIENCES

- **Quality Control Manager at** Ministry of **Digital Economy and Entrepreneurship (MoDEE), e-government program** since January 2017 dealing with several tasks **working on e-transformation Projects in national level.**
- **Protection Information Management and Reporting Officer at UNRWA** - Protection and Neutrality Unit - Jordan, acting as Activity Info Focal point in JFO April 2016 – December 2016.
- **Consultant of Project Management and Quality Assurance** December 2013 to July 2017; **Participating in** implementing **projects** funded by **STRD, EU, ZJU** and **JU**:

1. Estimation of PV energy generator using Data Mining and Artificial Neural network (ANN).
2. Energy efficiency and renewable energy integration using cloud computing. A case study: Computer center.
3. **Participate** in writing funded projects proposals: **KADDB, Erasmus+, SRTD, ERANTEMED, Horizon 2020, and USAID**.

- **Quality Assurance Engineer** at **InCube FZECO** UAE Company, Amman Office from May 2010 to August 2013.
- **Project Management Consultant** for Academic Research Archiving System for **Scientific Research Deanship in Jordanian University** from June 2009 to May 2010.

SKILLS

- Consultation in business project management and digital transformation.
- Build Releases, Quality Assurance, Data Base Design, System Analyst, and Software Development.
- Excellent ability of reporting.
- Writing Proposals for funded projects.
- Excellent Project Management, leadership skills.
- Team management, Negotiation, and Risk management.
- **Quality Control** and Software testing and **Use Software Testing Techniques** for desktop, web applications and mobile working on (**Windows, Android and iOS**).
- **Builds** Releases and Generate Product Packaging, Service Packs, and Patches.
- **Builds** useful Data Bases using Microsoft **SQL** Server2008/2012, and **Oracle** 10g /11g and deals with.
- **Audit for ISO9001 and ISO27001.**

Scholarships

- Scholarship award from Near East University (Yakın Doğu Üniversitesi), for **Ph.D. degree** in Business Administration 2020-2023.
- Scholarship award from Scientific Research Support Fund, Granting Academic Excellence for **Master degree** 2014-2016.
- Scholarship award from Ministry of Higher Education for **Bachelor degree** 2004-2009.

Awards

- Awarded First Place at HackthecrisisJO Entrepreneurship Hackathon for Covid-19 supported by TTI and WFP for 2020.
- Awarded First Place at Bedaya Entrepreneurship Program supported by Spark and the Dutch Embassy for 2019.

- Awarded Second Place at AAIS’ 2019 Arab Artificial Intelligence Summit in startup track challenge.
- Awarded the Best Research Award at Philadelphia University Research entitled "Integration of Renewable Energy with Cloud Computing" 2018.
- Awarded the short story prize for second place in the celebration of Jerusalem as the capital of Arab culture in Amman 2009.

Publications

Book:

Cloud Computing Adoption Challenges Case Study: Jordanian e-Government.
LAP LAMBERT Academic Publishing ISBN: 978-620-2-07608-1

Journals:

1- The Influence of Cloud Computing Adoption Challenges on e-Government Services.

2- Internet of Things - Architecture, Applications Challenges and A way to Standardization.

3- Harmonization between Renewable Energy and Cloud Computing towards Green Computing. A Case Study: Data Center at The University Of Jordan. In 2021 12th International Renewable Engineering Conference (IREC) (pp. 1-5). IEEE.

4- The Influence of Machine Learning on Enhancing Rational Decision-Making and Trust Levels in e-Government. Systems, 12(9), 373.

LANGUAGES

- Arabic (Native)
- English (Professional working proficiency).